Spatio-Temporal Modelling of Informal Settlement Using GIS and CA-Markov Model; A Case of Dire Dawa City, Ethiopia

Zekarias Wondimu

Thesis submitted to the Department of Architecture

College of Civil Engineering and Architecture (CoCEA)

Office of Graduate Studies

Adama Science and Technology University

June, 2025

Adama, Ethiopia

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Under the Supervision of

Dejene Tesema (PhD)

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DECLARATION

I hereby declare that this research thesis entitled "**Spatio-Temporal Modelling of Informal Settlement Using GIS and CA-Markov Model; A Case of Dire Dawa City, Ethiopia**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All materials used for this thesis have been duly acknowledged through citation.

Zekarias Wondimu	________________________	________________
Name of student	Signature	Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read this thesis entitled "**Spatio-Temporal Modelling of Informal Settlement Using GIS and CA-Markov Model; A Case of Dire Dawa City, Ethiopia**" prepared under my guidance by Zekarias Wondimu submitted in partial fulfillment of the requirements for the degree of Master's in **Geoinformatics Engineering**. Therefore, I recommend the submission to the department following the applicable procedures.

Dejene Tessema (PhD)	_________________	________________
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APPROVAL PAGE OF THE THESIS

I, the advisor of the thesis entitled "**Spatio-Temporal Modelling of Informal Settlement Using GIS and CA-Markov Model; A Case of Dire Dawa City, Ethiopia"** and developed by Zekarias Wondimu hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Major Advisor Signature Date

We, the undersigned, members of the Board of Examiners of the thesis by Zekarias Wondimu have read and evaluated the thesis entitled "**Spatio-Temporal Modelling of Informal Settlement Using GIS and CA-Markov Model; A Case of Dire Dawa City, Ethiopia"** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the degree requirement of Master of Science in **Geoinformatics Engineering**.

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Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and College Graduate Committee (CGC).

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ACRONYMS AND ABBREVIATIONS

Acronym	Full Form
BAI	Built-Up Area Index
CBD	Central Business District
CA-Markov	Cellular Automata-Markov Model
GCPs	Ground Control Points
GIS	Geographic Information Systems
IHDP	Integrated Housing Development Program
LULC	Land Use/Land Cover
NDBI	Normalized Difference Built-Up Index
NIR	Near-Infrared
RF	Random Forest
RGB	Red, Green, Blue (color bands for imagery)
SDGs	Sustainable Development Goals
SOCEA	School of Civil Engineering and Architecture
SWIR	Shortwave Infrared
UI	Urban Index
USGS	United States Geological Survey

Abstract

Informal settlements are urban areas where residents live in conditions without legal recognition of land tenure. This research is aimed to model the spatio-temporal dynamics of informal settlements using GIS and CA-Markov model in Dire Dawa City, Ethiopia. This study utilized satellite imagery from the Landsat 5 MSS (1994), Landsat 7 ETM+ (2004), and Landsat 8 OLI/TIRS for 2014 and 2024. The Random Forest (RF) algorithm was used for classification due to its robustness and accuracy in handling complex remote sensing data. Preprocessing steps, including clipping, cloud and shadow masking, radiometric and geometric correction, were applied to ensure the accuracy of the Landsat imagery. Change detection was conducted using post-classification comparison, where independent classifications for each period were compared to identify areas of change. Landscape metrices such as Edge density, Largest Patch Index, Fractal dimension index and compactness were employed to detect informal settlements. CA-Markov model was used to predict the expansion of informal settlements. Findings of the research revealed that, over the past 30 years, Dire Dawa City has seen notable land cover changes. From 1994 to 2024, Dire Dawa experienced significant land use changes. Agricultural land grew moderately from 8.31% to 15.14%, and urban areas expanded from 0.07% to 2.20%. The analysis of landscape metrics across eight urban zones (1994, 2004, 2014, and 2024) reveals significant growth of informal settlements. Edge density increased by 15-25% across all zones, with patches in Zone 1 and Zone 7 growing by 40-50%. The spatial complexity, measured by the shape index, rose by 10-20% in Zones 3 and 6. Zones 1, 6, 7, and 8 experienced rapid expansion. From 2024 to 2054, Dire Dawa will experience significant land use changes. Built-up areas will increase from 2.20% to 6.88%, and agricultural land will grow substantially from 15.14% to 38.94%. This study highlights how geospatial technologies, including GIS and CA-Markov modeling, effectively analyze and predict the expansion of informal settlements. The integration of satellite imagery, machine learning, and spatial metrics provided detailed insights into land use dynamics in Dire Dawa over the past and future decades. The 2054 simulation predicts more urban and agricultural growth, along with further shrubland loss. The trained CA-Markov model offers reliable future projections, highlighting the need for sustainable land management and conservation strategies.

Keywords: CA-Markov Model, Informal settlement, Landscape Metrices, Land use/cover

CHAPTER ONE

1. INTRODUCTION

1.1.Background of the study

The growth of informal settlements is largely driven by the rapid influx of people migrating to urban areas and the inability of the urban poor to afford formal housing options (Wekesa et al., 2010). In response to the social, cultural, and economic challenges they face, informal settlers seek out available land that provides better access to employment opportunities. These settlements are typically established in areas influenced by several key physical factors. First, they are often located near major transport networks, such as highways, roads, railways, rivers, and canals, which facilitate mobility and access. Second, they are situated close to places offering employment, such as the city's central business district (CBD), industrial zones, or wealthier neighborhoods. Finally, the proximity to both transport networks and employment opportunities is considered the most significant factor influencing the establishment of these settlements (Dubovyk et al., 2010).

Informal settlements have expanded rapidly in recent decades, driven by ongoing socioeconomic changes and urbanization. It is estimated that nearly 25% of the global urban population now lives in informal settlements, with this number expected to increase in the future (Aboulnaga et al., 2021). Despite their growing prevalence, informal settlements remain a marginalized priority in urban planning, policymaking, and development efforts (Arimah, 2011; Samper et al., 2020). These settlements are commonly located on the outskirts of cities, occupying underutilized land or areas unsuitable for formal development, such as steep slopes or wetlands (Dovey & King, 2011). While informal settlements are a defining characteristic of urbanization in the Global South, detailed knowledge of their spatial and temporal dynamics is often scarce. Life within these settlements is often marked by precarity and a sense of invisibility, exacerbated by limited access to public services and fragmented physical connections to the rest of the city. However, despite these challenges, informal settlements and their inhabitants remain deeply integrated socially and economically with the broader urban environment, suggesting that "most developing cities are unsustainable without them" (Dovey & King, 2011). Additionally, informal settlements play a crucial role in hazard and risk mitigation, addressing major health and environmental challenges.

Urbanization is a global phenomenon with significant socio-economic and environmental implications. In developing countries, rapid urbanization often results in the emergence and expansion of informal settlements due to inadequate housing and planning systems (UN-Habitat, 2020). Informal settlements are characterized by unplanned development, poor infrastructure, and a lack of basic services, posing significant challenges to sustainable urban management (Angel et al., 2011). Understanding the spatial and temporal dynamics of such settlements is crucial for effective urban planning and policy formulation.

Geospatial technologies, such as Geographic Information Systems (GIS), coupled with predictive models like the Cellular Automata-Markov (CA-Markov) model, provide powerful tools for analyzing and forecasting land use changes (Eastman, 2012). These models are widely applied to simulate the spatial evolution of urban areas and to predict future trends based on historical data. In Ethiopia, cities like Dire Dawa face challenges related to rapid urban growth and informal settlement expansion, necessitating advanced methodologies to manage and plan urban spaces effectively (Mengistu, 2018).

This study employs GIS and the CA-Markov model to analyze and predict the spatio-temporal dynamics of informal settlements in Dire Dawa City. By integrating spatial data and modeling techniques, this research aims to provide valuable insights into the factors driving informal settlement growth and to support informed decision-making for sustainable urban development.

1.2. Statement of the problem

Globally, informal settlements have become a significant challenge in urban management, particularly in developing countries. Studies conducted in Latin America, Asia, and Africa highlight the complexities associated with informal settlements, including their rapid and unregulated growth, lack of basic services, and socio-economic inequalities. For instance, in Rio de Janeiro, Brazil, informal settlements, known as favelas, have expanded due to economic disparities, rural-to-urban migration, and limited affordable housing options (UN-Habitat, 2016). Similarly, in Dhaka, Bangladesh, informal settlements house a significant portion of the urban population, leading to overcrowding and severe environmental degradation (Rahman et al., 2019). While these studies have contributed to a better understanding of informal settlement dynamics, they often focus on the socio-economic factors rather than integrating spatial-temporal modeling to predict future growth patterns.

In Africa, informal settlements are particularly prevalent in rapidly urbanizing regions. Studies in cities such as Nairobi, Kenya, and Lagos, Nigeria, have examined the drivers of informal settlement formation, including rural-to-urban migration, poverty, and inadequate urban planning frameworks. Wachira et al. (2020) demonstrated the application of the CA-Markov model in Nairobi to predict urban sprawl and the emergence of informal settlements. Their findings provided insights into the spatial distribution of future growth hotspots, enabling urban planners to prioritize areas for intervention. Similarly, Adebayo et al. (2018) analyzed the expansion of informal settlements in Lagos using remote sensing and GIS, highlighting the role of weak governance and land tenure systems. While these studies underscore the utility of advanced spatial modeling in urban planning, they reveal a gap in understanding the temporal dynamics and localized factors influencing settlement growth in different African contexts.

In Ethiopia, informal settlements are a pressing issue in major urban centers such as Addis Ababa, Hawassa, and Dire Dawa. Studies have identified rapid population growth, rural-to-urban migration, and limited housing options as key drivers of unregulated urban expansion (World Bank, 2015). Woldegerima et al. (2017) investigated the environmental impacts of informal settlements in Addis Ababa, finding that settlement expansion on marginal lands exacerbates soil erosion and flooding risks. Abebe (2013) examined the governance challenges in addressing informal settlements, highlighting the inadequacy of existing urban planning policies that rely on static datasets. Despite these efforts, few studies have integrated spatial and temporal analyses to predict the growth dynamics of informal settlements. In Dire Dawa, the growth of informal settlements remains under-researched. Existing literature focuses primarily on the socio-economic impacts of informal settlements but fails to account for the spatial dynamics of their expansion. For instance, while Tesfaye et al. (2021) explored the challenges of informal settlements in the city, their study lacked predictive modeling approaches to forecast future trends. This gap highlights the need for comprehensive studies that combine GIS and advanced spatial models like the CA-Markov model to analyze settlement patterns and inform urban planning strategies effectively.

The CA-Markov model, which integrates the spatial dynamics of Cellular Automata with the probabilistic forecasting capabilities of the Markov chain, has been widely applied in developing countries to predict settlement patterns and inform land use planning. For instance, in Nairobi, Kenya, the CA-Markov model was utilized to forecast the growth of informal settlements by identifying areas most susceptible to urban sprawl, thereby enabling targeted infrastructure planning and resource allocation (Wachira et al., 2020). Similar applications have been demonstrated across Ethiopia. In Gondar City, the model effectively simulated urban land use dynamics, offering critical insights for future urban planning (Beyene & Minale, 2023). In the Gumara Watershed of the Upper Blue Nile Basin, scenario-based modeling using CA-Markov revealed potential land cover changes under different development trajectories (Belay et al., 2024). Likewise, in Raya, northern Ethiopia, the model predicted land use and land cover scenarios from 2015 to 2033, aiding in sustainable land management strategies (Gidey et al., 2017). The Upper Awash Basin has also benefited from CA-Markov modeling, which provided projections of land use and land cover dynamics under various policy and environmental scenarios (Gebresellase et al., 2023). These studies collectively underscore the utility of CA-Markov modeling in guiding proactive urban and environmental planning through informed scenario analysis and spatial prediction.

While the CA-Markov model has been widely employed to simulate land use and land cover (LULC) dynamics in various regions, existing studies have largely concentrated on broad-scale environmental changes rather than the specific dynamics of informal settlement growth. For example, studies in Ethiopia—such as those conducted in Gondar City (Beyene & Minale, 2023), the Gumara Watershed (Belay et al., 2024), Raya (Gidey et al., 2017), and the Upper Awash Basin (Gebresellase et al., 2023)—have effectively utilized the CA-Markov model to project future LULC scenarios. However, these applications primarily focus on changes in agricultural land, forest cover, and urban expansion at a macro level, without directly addressing the spatial and social complexities of informal settlements. As such, they fall short in leveraging the CA-Markov model's potential for predicting informal settlement formation and expansion, which requires integrating fine-scale urban dynamics, socio-economic drivers, and spatial informality patterns. This highlights a significant knowledge gap in current literature, where the CA-Markov model remains underutilized for informal settlement analysis and targeted urban policy planning.

1.3. Objective of the study

1.3.1. General Objective

The general objective of this study is to analyze and model the spatio-temporal dynamics of informal settlements in Dire Dawa City, Ethiopia, by integrating geospatial techniques and the CA-Markov model to support informed urban planning and sustainable land management decisions.

1.3.2. Specific Objectives

- To analyze spatio-temporal dynamics of land use/cover dynamics over the past 30 years (1994-2024).
- To detect informal settlement dynamics using different spectral metrice over time (1994-2024)
- To integrate GIS with the CA-Markov model to predict future land use and settlement expansion.

1.4. Research questions

1. How have the spatio-temporal dynamics of land use and land cover changed in Dire Dawa City over the past 30 years (1994–2024)?
2. What are the trends and patterns in informal settlement dynamics as detected using different spatial metrices from 1994 to 2024?
3. How can GIS and the CA-Markov model be integrated to predict future land use and settlement expansion in Dire Dawa City?

1.5. Significance of the study

This study holds significant academic, practical, and policy-oriented relevance. Academically, it contributes to the growing body of literature on urban informality and spatial modeling by demonstrating the application of GIS and CA-Markov models in an Ethiopian context. It provides a methodological framework for analyzing and predicting informal settlement dynamics, which can be replicated in other cities facing similar challenges.

Practically, the research outputs will equip urban planners and local government authorities in Dire Dawa with actionable insights to address the challenges posed by informal settlements. By identifying hotspots of informal settlement growth and simulating future scenarios, the study will support evidence-based decision-making and resource allocation.

From a policy perspective, this research aligns with Ethiopia's urban development goals and the Sustainable Development Goals (SDGs), particularly Goal 11, which aims to make cities inclusive, safe, resilient, and sustainable. The findings will inform policy recommendations for managing urban growth, mitigating environmental risks, and promoting sustainable urban development in Dire Dawa City.

1.6.Scope and Delimitation of the Study

The scope of this study focuses on analyzing the spatio-temporal dynamics of informal settlements in Dire Dawa City, Ethiopia, using GIS and the CA-Markov model. It involves collecting spatial and temporal data, mapping current settlement patterns, assessing historical trends, and identifying key driving factors such as population growth and land use changes. The study further includes the integration of GIS with the CA-Markov model to simulate and predict future settlement patterns, validating model outputs, and providing actionable insights for urban planning and policy-making.

The delimitation of the study is confined to Dire Dawa City, focusing specifically on informal settlements and their spatial and temporal dynamics. It does not cover formal urban developments or settlements outside the city's jurisdiction. The analysis is based on available data, and the CA-Markov model's predictions are subject to the limitations of input data quality and model assumptions.

CHAPTER TWO

2. LITERATURE REVIEW

2.1.Definition and Challenges in Informal Settlements

Informal settlements represent areas of unregulated urban expansion, often developing without any formal planning and lacking essential infrastructure such as roads, electricity, water supply, and sanitation facilities. These areas typically arise in response to the pressures of rapid urbanization, soaring population growth, and entrenched socioeconomic inequalities, particularly in developing countries where urban planning and resource allocation struggle to keep pace with demand (UN-Habitat, 2020).

In Ethiopia, these issues are especially pronounced. As an economic hub, the city attracts a significant influx of rural migrants seeking better opportunities, resulting in the proliferation of informal settlements. This migration exacerbates the strain on already limited urban resources and creates challenges for urban governance. Informal settlements in Dire Dawa are marked by poor living conditions, with residents often facing limited or no access to basic services such as clean water, proper sanitation, and adequate housing (Angel et al., 2011). Moreover, the lack of legal recognition for these areas further complicates efforts to integrate them into formal urban frameworks. Addressing these multifaceted challenges requires a comprehensive understanding of the spatial patterns and temporal evolution of informal settlements. This insight is critical for formulating effective policies and interventions that can improve living conditions while promoting sustainable urban development.

2.2. Spatio-Temporal Dynamics of Urban Growth

Urban growth modeling plays a pivotal role in comprehending the complex dynamics of informal settlements. These settlements often emerge and expand in response to socioeconomic and environmental factors, making it essential to analyze their patterns of growth and evolution over time and space. Spatio-temporal analyses provide valuable insights into these processes by examining the interaction of spatial changes and temporal trends. By integrating time-series data with remote sensing techniques, researchers can effectively monitor and track the development of urban areas, offering a more detailed understanding of informal settlement dynamics (Herold et al., 2003).

For instance, in sub-Saharan Africa, spatial analysis has been widely employed to map urban expansion and identify the trends associated with informal settlements. Studies in this region have demonstrated how these methods can reveal the drivers and impacts of urbanization, highlighting patterns such as land use changes, population density shifts, and the encroachment of settlements into ecologically sensitive areas (Barredo & Demicheli, 2003). Such methodologies underscore the transformative potential of spatio-temporal analysis for evidence-based urban planning. By leveraging these tools, policymakers and urban planners can anticipate settlement growth, address infrastructure deficiencies, and develop strategies to promote sustainable urban development while mitigating the challenges associated with informal settlements.

2.3. GIS in Urban and Informal Settlement Studies

Geographic Information Systems (GIS) have significantly transformed the field of urban studies, offering advanced tools for the mapping, analysis, and visualization of spatial data. By enabling the integration of multi-temporal satellite imagery with demographic, socioeconomic, and environmental data, GIS has become an indispensable technology for studying and monitoring the growth and characteristics of informal settlements (Chapin & Kaiser, 1979). This integration allows researchers and urban planners to track changes over time, assess the implications of urbanization, and develop targeted interventions to address the challenges posed by these settlements.

In Ethiopia, GIS has been effectively employed to map and analyze the spatial distribution of informal settlements, providing critical insights into the patterns and drivers of urban sprawl. These analyses have revealed not only the extent of settlement expansion but also its impacts on local ecosystems, such as the encroachment on agricultural lands and environmentally sensitive areas (Yirsaw et al., 2017). By visualizing these trends, GIS facilitates a deeper understanding of the interplay between human activity and the natural environment. Moreover, it equips policymakers with data-driven tools to prioritize infrastructure development, allocate resources effectively, and plan for sustainable urban growth. The ability of GIS to synthesize complex datasets and generate actionable insights underscores its vital role in addressing the multifaceted challenges of informal settlement management and urban development.

2.4. CA-Markov Model in Urban Growth Prediction

The Cellular Automata (CA)-Markov model is a powerful tool for simulating and predicting urban land use changes by integrating the stochastic processes of the Markov chain with the spatial dynamics of Cellular Automata. This hybrid model has gained widespread use in urban studies due to its ability to capture both the probabilistic nature of land use transitions and the spatial interactions between land units. The Markov chain component models the likelihood of land use changes based on historical data, while the Cellular Automata component simulates the spatial patterns of these changes by considering the local interactions of neighboring cells, making the model particularly well-suited for simulating complex urban systems (Eastman, 2012).

In the context of informal settlements, the CA-Markov model has been demonstrated to effectively model the growth and spread of these areas by incorporating key driving factors such as population density, proximity to roads, access to infrastructure, and the influence of land use policies (Pijanowski et al., 2002). By integrating these variables, the model can simulate how informal settlements might expand based on these underlying dynamics. For instance, it can predict how shifts in population density or changes in infrastructure development may influence the spread of informal settlements in urban areas.

The predictive capability of the CA-Markov model makes it a valuable tool for urban planners and policymakers. By simulating future land use scenarios, the model can help planners understand potential trends in informal settlement growth, allowing for better forecasting and the development of targeted interventions. This is crucial for mitigating unplanned urbanization, as the model provides a framework to anticipate where and how informal settlements might expand, enabling proactive strategies for sustainable urban development, infrastructure planning, and resource management. The CA-Markov model's capacity to consider both spatial and temporal factors makes it an essential tool for managing the complexities of urban growth and addressing the challenges posed by informal settlements (Pijanowski et al., 2002).

2.5. Applications of CA-Markov Model in Developing Countries

The CA-Markov model has become a widely used tool for predicting urban land use changes and managing urban growth, particularly in developing countries where rapid urbanization and informal settlement growth present significant challenges. By integrating the spatial dynamics of Cellular Automata with the probabilistic capabilities of the Markov chain, this model enables researchers and urban planners to forecast land use changes and identify areas at risk of informal settlement expansion. Several studies have demonstrated the effectiveness of the CA-Markov model in the context of urbanization in developing countries, where the model has been applied to address specific challenges related to land use management, infrastructure planning, and informal settlement growth (Eastman, 2012).

One notable example is the application of the CA-Markov model in Nairobi, Kenya. In a study by Wachira et al. (2020), the model was used to predict future hotspots of informal settlement growth in the city. The researchers integrated factors such as population density, proximity to infrastructure, and land use policies to simulate the potential expansion of informal settlements. The study found that the CA-Markov model was effective in identifying areas that were likely to experience rapid urban sprawl, thus aiding in the development of targeted interventions to manage the growth of informal settlements. This predictive capability is crucial for urban planners in cities like Nairobi, where informal settlements are a significant concern due to rapid rural-to-urban migration and limited resources.

Similarly, in a study conducted in Accra, Ghana, the CA-Markov model was employed to forecast land use changes and assess the impact of urban expansion on informal settlement growth (Adelekan, 2017). The research integrated satellite imagery with socioeconomic data, enabling the model to simulate land use transitions and predict future settlement patterns. The results showed that the model was able to capture the complex interactions between socioeconomic factors, infrastructure availability, and environmental constraints, highlighting the potential of the CA-Markov model in informing sustainable urban development strategies in rapidly urbanizing regions.

2.6. Informal Settlements and Urban Policy in Ethiopia

Urban policies in Ethiopia have historically faced significant challenges in effectively addressing the rapid growth of informal settlements. These settlements, characterized by unplanned development and inadequate infrastructure, have emerged due to a combination of factors such as rapid urbanization, migration from rural areas, and limited housing options in urban centers. In response to these challenges, national programs such as the Integrated Housing Development

Program (IHDP) were introduced with the goal of providing affordable housing and improving the living conditions of urban residents, especially those in informal settlements. The IHDP has led to the construction of thousands of housing units, aiming to alleviate overcrowding and improve access to basic services like water and sanitation. However, these programs have not been entirely successful in addressing the root causes of informal settlement expansion, as they often fail to incorporate a comprehensive spatio-temporal perspective in their planning and execution (MoUDH, 2015).

2.7. Empirical Literature

The spatio-temporal modeling of informal settlements using GIS and the CA-Markov model has been a growing area of interest for urban planners and researchers, especially in the context of rapidly urbanizing cities in developing countries. Various studies have explored the application of Geographic Information Systems (GIS) and the CA-Markov model to understand the dynamics of informal settlements, identify drivers of urban sprawl, and predict future growth patterns, thereby informing more effective policy and decision-making processes.

One of the key studies in this area is by Pijanowski et al. (2002), who used GIS in conjunction with the CA-Markov model to predict land use changes in the southwestern United States. They demonstrated that integrating spatial data with temporal changes through the CA-Markov model could effectively forecast land use transitions, including urban expansion and the development of informal settlements. The study highlighted the model's potential in simulating growth patterns based on socioeconomic, environmental, and policy-driven factors. This approach was found to be highly valuable in urban planning, as it enabled stakeholders to anticipate future challenges in land management and resource allocation.

Similarly, Wachira et al. (2020) applied the CA-Markov model to simulate urban land use changes and identify potential hotspots for informal settlement growth in Nairobi, Kenya. Their study used spatial data derived from satellite imagery and incorporated demographic data to predict areas at high risk of informal settlement expansion. The results highlighted the effectiveness of the CA-Markov model in informing urban planning strategies, especially when combined with GIS to visualize and analyze the spatial dynamics of urban growth. By identifying future hotspots, the study emphasized how this modeling approach can guide targeted interventions and the sustainable management of informal settlements in growing cities.

In Accra, Ghana, Adelekan (2017) used the CA-Markov model to forecast the expansion of informal settlements and urban sprawl over a period of time. This study integrated multiple data sources, including satellite images and population growth projections, to simulate land use changes in the city. The model was successful in capturing the interaction of socioeconomic factors with physical space, providing a nuanced understanding of informal settlement dynamics. By simulating future scenarios of land use change, the study demonstrated how the CA-Markov model could inform policy decisions regarding the expansion of urban infrastructure and services, helping to mitigate the uncontrolled growth of informal settlements.

In Ethiopia, a country facing significant urban growth challenges, Yirsaw et al. (2017) used the CA-Markov model in Dire Dawa to predict land use changes and model the growth of informal settlements. The researchers integrated socio-economic data, population density trends, and land use policies to understand the dynamics of urban sprawl and informal settlement expansion. Their study emphasized the utility of combining GIS and CA-Markov modeling to inform policy decisions, suggesting that this approach could improve the management of urban growth and the allocation of resources for infrastructure development.

Sudhira et al. (2004) applied a similar method in Bangalore, India, using GIS and the CA-Markov model to predict land use changes and urban growth patterns. The study demonstrated how combining these tools could offer a comprehensive understanding of the spatial dynamics driving informal settlement growth. They used the model to forecast urban sprawl and informal settlements over time, revealing how land use changes were influenced by economic factors, migration, and local governance policies. This research pointed out that integrating GIS and CA-Markov modeling can significantly improve urban planning strategies, especially in rapidly expanding cities.

Another study by Zubair et al. (2020) in Karachi, Pakistan, used a similar approach to understand the urban sprawl and informal settlement dynamics. Their research highlighted how the CA-Markov model, in conjunction with GIS, could be applied to forecast the future of informal settlements by identifying vulnerable areas at risk of expansion. The study provided a comprehensive spatial analysis of urban land use and its potential shifts over time, showing that such modeling could guide the creation of policies aimed at controlling informal settlement growth, ensuring more equitable access to resources, and promoting sustainable urban development.

2.8. Research Gap

These studies collectively underscore the effectiveness of integrating GIS and the CA-Markov model in understanding and managing the dynamics of informal settlements in developing countries. By simulating future land use scenarios and identifying areas at risk of informal settlement expansion, this approach provides valuable insights for urban planners and policymakers, facilitating targeted interventions and sustainable urban development strategies.

However, despite the promising applications, there are notable research gaps in this field. Many studies have focused on specific regions or cities, often lacking generalizability to other contexts. Additionally, while the CA-Markov model effectively simulates land use changes, it may not fully capture the complexities of informal settlement dynamics, such as the influence of informal economies, social networks, and governance structures. Future research could address these gaps by incorporating a broader range of variables and applying the model to diverse urban settings to enhance its applicability and accuracy in predicting informal settlement growth.

CHAPTER THREE

3. MATERIALS AND METHOD

3.1. Description of the study area

Dire Dawa is in eastern Ethiopia, approximately 515 km from Addis Ababa. Geographically, the city lies between 9° 28′ 5.6″ and 9° 54′ 52.1″ N latitude and 42° 22′ 14.8″ and 41° 40′ 58.9″ E longitude. Dire Dawa is a major industrial and commercial hub, traversed by the Addis Ababa–Djibouti railway. The city's elevation ranges from 1,055 to 1,325 meters above mean sea level (a.m.s.l). According to data from the National Meteorological Agency (NMA), the region experiences a bi-modal rainfall pattern, with peak precipitation occurring in April and August. Monthly rainfall averages range from 5.7 mm in December to 118.6 mm in August, reflecting both spatial and temporal variability.

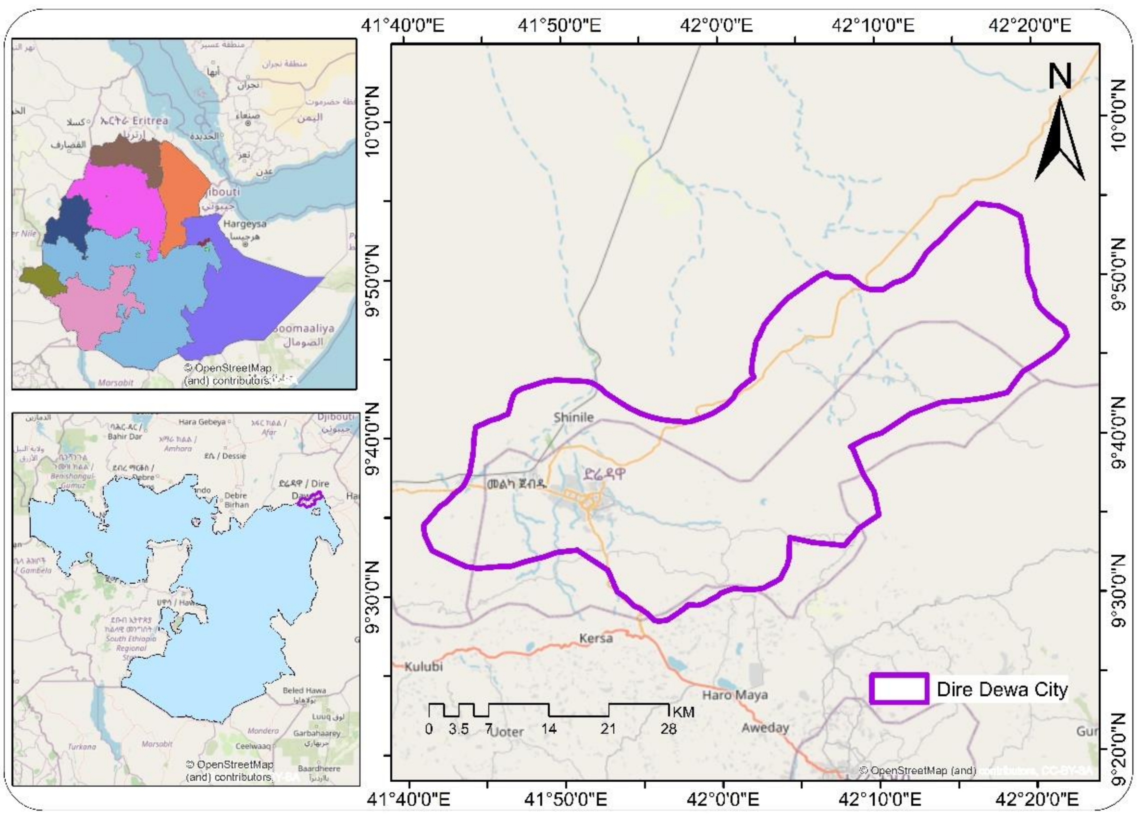


Figure 3-1: Location map of the study area

3.2.Research Approach

This study employs a quantitative research approach, as it involves the use of geospatial and statistical methods to model and analyze the spatio-temporal dynamics of informal settlements in Dire Dawa City. Quantitative methods are particularly well-suited for this type of research because they allow for precise measurements, spatial analysis, and predictive modeling, ensuring objectivity and replicability of results (Subbarayudu et al., 2024). The use of Geographic Information Systems (GIS) and the Cellular Automata-Markov (CA-Markov) model requires numerical data to map, simulate, and forecast patterns of informal settlements. The quantitative approach is appropriate because it provides a systematic means of understanding complex spatial phenomena and enables the use of advanced geospatial tools to produce accurate and scientifically sound results (Breunig et al., 2020). Additionally, this approach facilitates the integration of temporal data to assess changes over time and predict future trends in informal settlements (Hussainzad, 2024).

3.3.Research Design

The predictive research design was employed in this study, which used the CA-Markov model to simulate and forecast the spatiotemporal growth of informal settlements in Dire Dawa City. Historical land use/land cover (LULC) data was utilized to calibrate the model, generating a transition probability matrix to quantify the likelihood of land cover changes and incorporating spatial dynamics through Cellular Automata (Rimal et al., 2018). The model predicted future settlement patterns for specific timeframes (e.g., 2030, 2040) and allowed for scenario analysis to assess the impact of various policy interventions or urban planning strategies (Luo et al., 2020). Predicted maps were validated using recent LULC data to ensure reliability, providing forward-looking insights critical for urban planning and informed policymaking in managing informal settlements.

3.4.Data source and type

3.4.1. Satellite data

This research utilized satellite imagery from the Landsat and Sentinel-2 missions to perform a detailed spatiotemporal analysis of informal settlement growth in Dire Dawa City. The primary satellite data sources were the United States Geological Survey (USGS) platform and the Copernicus Open Access Hub. These platforms provided access to free, high-resolution, multispectral imagery, enabling robust land use/land cover (LULC) classification and change detection over multiple decades. The study focused on four key years: 1994, 2004, 2014, and 2024, chosen strategically to represent significant time intervals and socio-economic transformations in the city. The year 1994 was selected as the reference year, as it marked a period of rapid economic growth and population expansion in Dire Dawa, as reported by government documents. The subsequent years, 2004, 2014, and 2024, were included to analyze changes at consistent ten-year intervals, providing a comprehensive understanding of settlement dynamics over 30 years. Different satellite missions were used for each target year to ensure the highest quality data for that specific period. For 1994, Landsat 5 MSS imagery was utilized, as it provided reliable historical data for that era. For 2004, imagery from Landsat 7 ETM+ was employed, offering enhanced spatial and spectral resolution compared to its predecessor. The year 2014 used data from Landsat 8 OLI/TIRS, which delivered improved radiometric resolution and a broader spectral range for more precise land cover analysis. Finally, for 2024, the most recent Sentinel-2 MSI imagery was used, as it featured high temporal and spatial resolution, making it suitable for capturing current land cover dynamics.

Table 3-1: Satellite data type and source

S. N	Satellite	Sensor	Acquisition Date	Source
1	Landsat 5	MSS	15-Dec-1994	www.glovis.gov
2	Landsat 7	ETM+	18-Dec-2004	www.glovis.gov
3	Landsat 8	OLI/TIRS	20-Dec-2014	www.glovis.gov
4	Sentinel-2	MSI	22-Dec-2024	Open Access Hub

3.4.2. Reference data

To validate the accuracy of the classified land use/land cover (LULC) maps, Ground Control Points (GCPs) were collected using high-resolution imagery from Google Earth and additional global land cover datasets. Google Earth provided a time slider option, which allowed access to historical imagery. This feature enabled the extraction of GCPs for the selected years of study: 1994, 2004, and 2014, ensuring spatial consistency with the classified satellite imagery. For the most recent year, 2024, GCPs were collected directly from the most up-to-date Google Earth imagery. The time slider toolbar in Google Earth facilitated precise navigation through historical imagery, enabling the identification and collection of GCPs for specific land cover types. For instance, for the year 1994, the tool allowed the collection of points reflecting the land cover conditions of that time. Similarly, for 2004 and 2014, the same method was applied to ensure alignment with the classified imagery for those years. For 2024, GCPs reflected current land cover conditions and were gathered based on the latest high-resolution images available on Google Earth. In addition to Google Earth-derived GCPs, global land cover datasets such as the Global Land Cover Map (2015–2014) were used as supplementary reference data. To ensure a robust and comprehensive validation process, 100 GCPs were collected for each land use/land cover class for each study year. With five land use/land cover categories selected for analysis, a total of 500 GCPs were gathered for each year.

3.4.3. Training data for classification

The training data required for the classification algorithm were collected directly from RGB imagery of each study year within the Google Earth Engine (GEE) platform. The quality and accuracy of the classification largely depended on the representativeness and quantity of the training points selected for each land use/land cover (LULC) class. The number of training points for each class varied depending on the visual characteristics of features observed in the RGB imagery. For land cover types with homogeneous spectral characteristics, which were challenging to distinguish from one another (e.g., barren land and sparsely vegetated areas), a larger number of training points were collected. This approach ensured better representation of subtle differences and reduced classification errors, as suggested by previous studies (Foody, 2002; Belgiu & Drăguţ, 2016). Conversely, for easily identifiable features based on distinct spectral signatures and spatial characteristics (e.g., water bodies or urban areas), fewer training points sufficed to achieve accurate classification results. The selection of training points followed best practices recommended in the literature, emphasizing even distribution across the study area and representation of class variability (Congalton & Green, 2019). Training data were drawn from multiple locations within each LULC category to account for intra-class variability and improve the robustness of the classification. A minimum of 30 training points per class was established as a baseline, as suggested by the rule of thumb for remote sensing classification tasks (Campbell & Wynne, 2011). For classes with high variability or spectral overlap, this number was increased accordingly.

3.5.Method of data analysis

3.5.1. Preprocessing

Preprocessing of Landsat imagery was critical to ensure accurate analysis of informal settlement growth in Dire Dawa City. Initially, the imagery was clipped to the region of interest, focusing on the city area to improve computational efficiency and target relevant land cover types (Zhang et al., 2020). Cloud and shadow masking were performed to eliminate irrelevant features that could distort land cover classification, as unmasked clouds could interfere with spectral signals (Chai et al., 2019; Klemas et al., 2013). Radiometric correction was applied to adjust for atmospheric and sensor-related distortions, ensuring consistent reflectance values across images from different years and sensors, which was essential for accurate comparison (Du et al., 2019). Geometric correction aligned the satellite images with geographical coordinates to account for distortions from sensor errors and terrain effects, ensuring accurate spatial alignment for change detection (Liu et al., 2015). These preprocessing steps, including clipping, masking, radiometric correction, and geometric correction, enhanced the quality of the classified land use/land cover (LULC) maps, ensuring reliable analysis of settlement dynamics over time.

3.5.2. Land use/cover classification

This research employed the Random Forest (RF) algorithm for land use/cover classification due to its strong performance, robustness, and versatility in handling complex remote sensing datasets. RF is an ensemble learning method that builds multiple decision trees and combines their outputs to make predictions. This approach proved particularly effective in land cover classification tasks, where complex relationships exist between input features (such as spectral bands and indices like NDVI) and land cover types. RF was widely used in remote sensing applications due to its high classification accuracy, even in the presence of noisy or incomplete data (Breiman, 2001). The algorithm handled large datasets well, which was crucial when working with satellite imagery containing a vast number of features (bands, indices) and spatial complexities. RF consistently outperformed many other classifiers like support vector machines (SVM) and k-nearest neighbors (KNN) in various studies (Gislason et al., 2006).

One key advantage of RF was its ability to handle non-linear relationships and interactions among features, which are common in remote sensing data. Remote sensing data often exhibit complex, non-linear relationships between features, making it difficult for simpler classifiers to distinguish between land cover types. RF captured these non-linearities effectively due to its ensemble structure of decision trees (Liaw & Wiener, 2002). This made RF well-suited for applications involving varied land cover classes, such as urban areas, forests, water bodies, and barren land. RF also effectively dealt with imbalanced datasets, where certain land cover classes may be underrepresented in the training data. This was especially useful for classifying informal settlements, which might have sparse or non-continuous patterns in satellite imagery. The algorithm generated multiple decision trees, allowing for a more generalized and balanced classification (Cutler et al., 2007). Additionally, RF provided the ability to assess the importance of various features used for classification, which helped identify the spectral bands or indices that contributed most to distinguishing land cover classes, offering valuable insights for further analysis (Liaw & Wiener, 2002).

Random Forest operates through an ensemble of decision trees. The basic steps of the algorithm can be represented as follows:

1. **Bootstrap Aggregating (Bagging):** Create N bootstrap samples (random samples with replacement) from the training dataset D.

2. **Tree Construction:** For each bootstrap sample D_i, build a decision tree T_i using a random subset of features F_i at each node.

3. **Majority Voting:** For classification, the final prediction $\hat{y}$ for a new data point, x is obtained by majority voting overall N trees:

$$\hat{y} = Majority\ vote\ (T_1(x), (T_2(x), \ldots, T_n(x)) \qquad \text{Equation 3-1}$$

4. **Final Decision:** The predicted class label $\hat{y}$ is the mode (most frequent class) of the predicted labels from all trees.

3.5.3. Accuracy Assessments

Accuracy assessment is a critical component of remote sensing classification, as it provides the necessary validation to ensure the reliability of the classified land use/land cover (LULC) maps (Rwanga, 2017). The goal is to quantify the accuracy of the classification results by comparing the predicted land cover classes with reference data, typically collected from high-resolution Google earth imagery and existing Global land cover maps. In this study, the accuracy assessment will be conducted by computing several statistical measures, such as overall accuracy, producer's accuracy, user's accuracy, and the Kappa coefficient.

Overall Accuracy: The overall accuracy is the most common and simplest measure used to assess the accuracy of classified maps. It represents the percentage of correctly classified pixels over the total number of pixels. It can be calculated as:

$$Overall\ accuracy = \frac{Number\ of\ Correctly\ classified\ pixel}{Total\ Number\ of\ pixels} * 100 \qquad \text{Equation 3-2}$$

Producer's Accuracy: Producer's accuracy, also known as recall or sensitivity, measures how well the classifier is at correctly identifying instances of a particular land cover class. It is calculated by dividing the number of correctly classified pixels of a specific class by the total number of pixels that actually belong to that class in the reference data:

$$Producer\ accuracy = \frac{Number\ of\ Correctly\ classified\ pixel\ in\ Class}{Total\ Number\ of\ pixels\ in\ class} * 100 \qquad \text{Equation 3-3}$$

User's Accuracy: User's accuracy, or precision, measures how many of the pixels classified into a particular class are actually correct. It is calculated by dividing the number of correctly classified pixels of a class by the total number of pixels that were classified as that class:

$$User\ accuracy = \frac{Number\ of\ Correctly\ classified\ pixel\ in\ Class}{Total\ Number\ of\ pixels\ as\ class} * 100 \qquad \text{Equation 3-4}$$

Kappa Coefficient: The Kappa coefficient is a more sophisticated metric that accounts for agreement occurring by chance. It measures the proportion of agreement between the reference data and the classified data after correcting for random chance. The Kappa coefficient is calculated as:

$$k = \frac{p_o - p_e}{1 - p_e} \qquad \text{Equation 3-5}$$

where:

- p_o is the observed agreement (overall accuracy),
- p_e is the expected agreement (the probability of chance agreement).

A Kappa value close to 1 indicates almost perfect agreement, while a value close to 0 indicates no agreement beyond chance.

3.5.4. Change detection

Change detection is a vital process in remote sensing, used to identify and quantify changes in the landscape over time (Willis, 2015). In this study, change detection was employed to analyze the growth of informal settlements in Dire Dawa City over four key years: 1994, 2004, 2014, and 2024. The research evaluated the spatial extent and dynamics of settlement growth and transformation by comparing land use/land cover (LULC) maps derived from satellite imagery for each of these years. One of the most commonly used techniques for change detection in land cover analysis is the post-classification comparison, where independent classifications were conducted for each period, and the classified images were compared to identify areas of change. This method allowed for the generation of detailed maps that showed areas of change and non-change, providing a clear spatial representation of how land cover evolved. The change detection matrix (a change matrix) was constructed by comparing the classified maps from two different periods. Each cell in the matrix represented the number of pixels that had shifted from one class to another.

$$Change\ Matrix = \begin{bmatrix} Class\ 1\ in\ Year\ 1 & Class\ 2\ in\ year\ 1 \ldots \\ Class\ 1\ in\ year\ 2 & Class\ 2\ in\ year\ 2 \ldots \end{bmatrix} \qquad \text{Equation 3-6}$$

From this matrix, the change detection rate for each class can be calculated:

$$Change\ Rate = \frac{Number\ of\ Changed\ Pixels}{Total\ Number\ of\ Pixels} * 100 \qquad \text{Equation 3-7}$$

3.5.5. Future Scenarios

CA-Markov model

The CA-Markov model is a hybrid modeling approach that combines Cellular Automata (CA) with the Markov chain model, making it an effective tool for predicting and simulating land use/land cover (LULC) changes, including the growth of informal settlements (Ghosh et al., 2017; Subedi et al., 2013; Solaimani, 2024). The model is particularly useful for forecasting future scenarios, such as the expansion of informal settlements in urban areas like Dire Dawa City.

Markov Chain Model

The Markov chain model is used to describe the probability of transitioning from one land use state to another over a specified period (Hamad et al., 2018). This model utilizes historical land use data to generate a transition probability matrix, which quantifies the likelihood of each land use class changing to another. For instance, it can predict the probability of a rural area transitioning into urban or informal settlement land based on past land use changes. This transition matrix is derived from analyzing land cover changes over a period, and it can then be used to forecast how land use classes will evolve over time. The general formula for the transition matrix in a Markov chain model is:

$$P(1+t) = P(t) * T \qquad \text{Equation 3-8}$$

Where:

- $P(t)$ is the current state of land cover at time t,
- T is the transition probability matrix,
- $P(t+1)$ is the predicted state of land cover at time $t+1$.

Cellular Automata (CA) Model

The Cellular Automata (CA) model simulates spatial processes through a grid of cells, each representing a land unit (Sante et al., 2015). The state of each cell evolves over time based on predefined rules that consider the current state of the cell and the states of its neighboring cells. The rules simulate spatial phenomena, such as the spread of urbanization or informal settlements. In the context of informal settlement growth, CA helps simulate how new areas are likely to be converted into informal settlements due to processes like encroachment or the absence of planned urban development. The model incorporates the influence of neighboring cells, meaning that areas adjacent to already established urban zones have a higher likelihood of developing into informal settlements. The state of each cell in the CA model is updated based on a set of rules, which may involve a simple majority rule or more complex spatial rules.

$$S_{i,j}(t+1) = f(S_{i,j}(t), Neighbors\ of\ S_{i,j}) \quad \text{Equation 3-9}$$

Where:

- $Si, j(t)$ is the state of the cell (i, j) at time t,
- $f()$ represents the transition function,
- Neighbors of Si, j influence the next state of the cell.

3.6.Data analysis procedure (Flowchart of the study)

The methodological flowchart (Figure 3-2) of this research begins with the collection of high-resolution RGB images from Google Earth, which serve as a base for obtaining Ground Control Points (GCPs). These GCPs are crucial for accurate geo-referencing of the satellite imagery, ensuring that subsequent analyses are spatially correct. The GCPs are identified by comparing the high-resolution images with the satellite data, allowing for precise alignment and calibration of the satellite imagery.

Next, satellite images from four distinct time points (1994, 2004, 2014, and 2024) are acquired. These include Landsat 5 MSS imagery for 1994, Landsat 7 ETM+ for 2004, Landsat 8 OLI/TIRS for 2014, and Sentinel 2 MSI for 2024. Each satellite mission offers different spatial and spectral resolution, and these images provide a temporal overview of the study area. The images are sourced from relevant platforms, including the USGS for Landsat and the Copernicus Open Access Hub for Sentinel-2 data.

Once the satellite images are obtained, they undergo several preprocessing steps. The images are clipped to the boundary of Dire Dawa City to focus the analysis on the relevant urban area. Masking is then applied to remove unwanted features such as clouds and shadows that might interfere with the classification process. Radiometric correction follows, adjusting the pixel values to correct for sensor errors, atmospheric conditions, and lighting variations. Finally, geometric correction is performed to address any distortions in the satellite images, ensuring they are spatially accurate and aligned with real-world coordinates.

The next step involves the collection of training samples. RGB imagery from Google Earth is used to identify representative sample points for various land cover classes, such as formal and informal settlements. These sample points are critical for training the Random Forest (RF) classification algorithm, which is used to classify the satellite images into different land cover types. The RF algorithm is chosen for its ability to handle large datasets, reduce overfitting, and deliver reliable, accurate results. Following the classification process, three spectral indices NDBI (Normalized Difference Built-up Index), BAI (Bare Area Index), and UI (Urban Index) are calculated. These indices are used to enhance the classification results by distinguishing between different land use types, particularly formal and informal settlements.

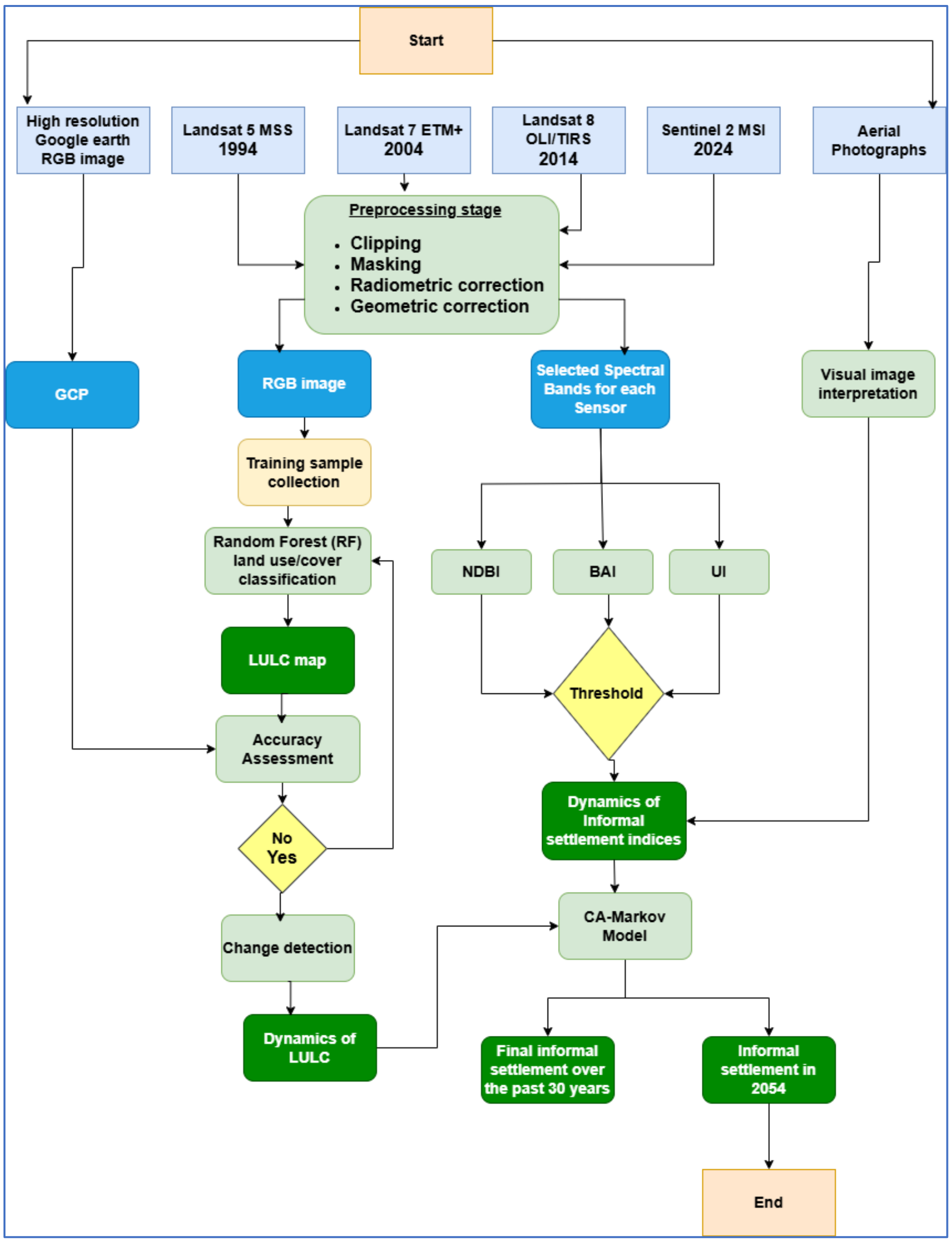


Figure 3-2: Methodological flowchart of the study

After generating the land cover classification map and calculating the spectral indices, an accuracy assessment is performed to evaluate the quality of the classification. This is done by comparing the classified map with ground truth data and calculating various accuracy metrics, such as overall accuracy and Kappa coefficient. If the accuracy is unsatisfactory, adjustments to the training samples, classification algorithm, or preprocessing steps are made to improve the results.

The next step is change detection, where the land cover maps from different years are compared to identify areas that have changed over time. Change detection helps track informal settlements' growth and understand how urban areas have evolved. Thresholding is applied to define the significance of these changes, specifically targeting the expansion of informal settlements. Once the changes are detected, the dynamics of informal settlement indices are analyzed to understand their spread and growth patterns over time. This step provides insights into the factors driving informal settlement growth and helps predict future trends.

The final stage of the flowchart involves the use of the CA-Markov model to predict the future distribution of informal settlements in 2054. This model combines the Cellular Automata (CA) and Markov Chain models, simulating future land cover changes based on historical data and spatial patterns. The CA-Markov model accounts for spatial autocorrelation, where the land cover of one area influences its neighboring areas. This approach is particularly useful for modeling the growth of informal settlements, offering a future perspective based on current trends.

Finally, the prediction of informal settlements for 2054 is generated. This forecast shows the expected spread of informal settlements over the next 30 years, providing valuable information for urban planning and policy development. The methodology concludes with the presentation of this final predicted map, offering insights into future urban dynamics in Dire Dawa City.

CHAPTER FOUR

4. RESULT AND DISCUSSIONS

4.1. Results

Dynamic of land use land cover over the past 30 years (1994-2024) in Dire Dewa City. Over the last three decades, Dire Dawa City has experienced intense land use and land cover (LULC) changes that have reorganized its landscape as a result of urbanization, population pressure, and climate change. The analysis considers four most critical periods of time (1994, 2004, 2014, 2024) and shows shifting dynamics between built-up lands, agriculture, forest, shrubland, and bareland.

4.2.Dynamics of LULC over the past 30 years (1994-2024)

4.2.1. LULC in 1994

In 1994, Dire Dawa was dominated by natural covers, and most of these were shrubland (around 50.31%) and forest (32.73%). The expansive natural covers provided important ecosystem services including support to biodiversity, carbon sequestration, and protection of soil.

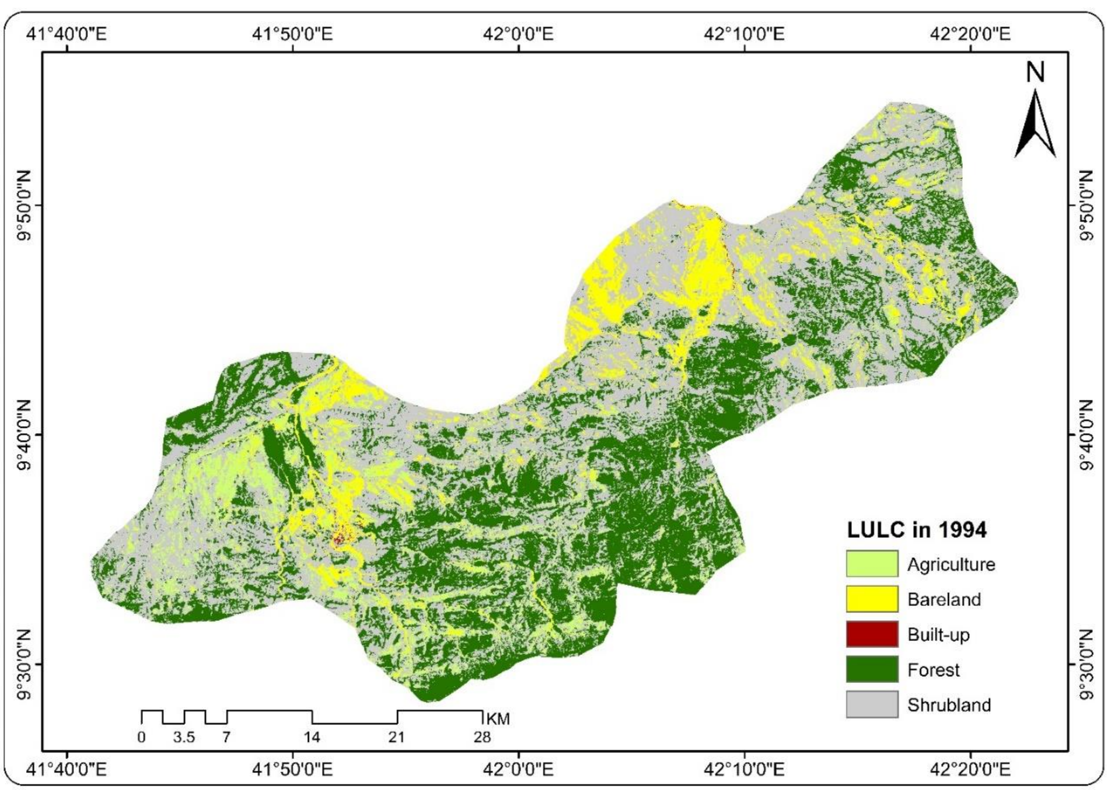


Figure 4-1: LULC in 1994

In 1994, Dire Dawa was dominated by natural covers, and most of these were shrubland (around 50.31%) and forest (32.73%). The expansive natural covers provided important ecosystem services including support to biodiversity, carbon sequestration, and protection of soil. In 1994, Dire Dawa was dominated by natural covers, and most of these were shrubland (around 50.31%) and forest (32.73%). The expansive natural covers provided important ecosystem services including support to biodiversity, carbon sequestration, and protection of soil. Farm land covered proportionally small area, i.e., 8.31%, which revealed moderate intensity of farming activities. Bareland represented 8.59%, reflecting some unused or degraded lands. Urbanized areas were observed only at a paltry 0.07%, indicating tiny amounts of urban infrastructure and practically zero slum formation. The year of reference here is that of a semi-natural state, with the primarily undisturbed human interventions still being modest.

Table 4-1: Land use land cover area and percentage for the selected years (1994, 2004, 2014, and 2024) in Dire Dewa City

	1994		2004		2014		2024	
Class	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
Builtup	102.31	0.07	248.84	0.16	1830.19	1.19	3377.19	2.20
Agriculture	12762.04	8.31	29524.83	19.23	19458.77	12.67	23241.20	15.14
Forest	50253.18	32.73	28583.63	18.62	16298.67	10.61	9764.43	6.36
Shrubland	77243.33	50.31	83946.63	54.67	112299.03	73.14	116104.59	75.61
Bareland	13186.70	8.59	11243.62	7.32	3660.89	2.38	1060.14	0.69
Total	153547.55	100.00	153547.55	100.00	153547.55	100.00	153547.55	100.00

4.2.2. LULC in 2004

Land cover patterns up to 2004 had significantly altered. Vegetation had risen to 54.6%, indicating steadily more forests or fields of cultivation encroaching into lower vegetative covers. Forest cover reduced to 17.1%, indicating the impact of deforestation, perhaps due to fuelwood cutting, charcoal production, and the clearing of land for agriculture. Agricultural land rose considerably to 19.23%, indicating rising food production needs perhaps fueled by population growth. Bareland fell slightly to 8.3%, and built-up areas, though still low at 0.21%, indicated the first signs of expansion, indicating the early stages of urban sprawl and informal settlement expansion.

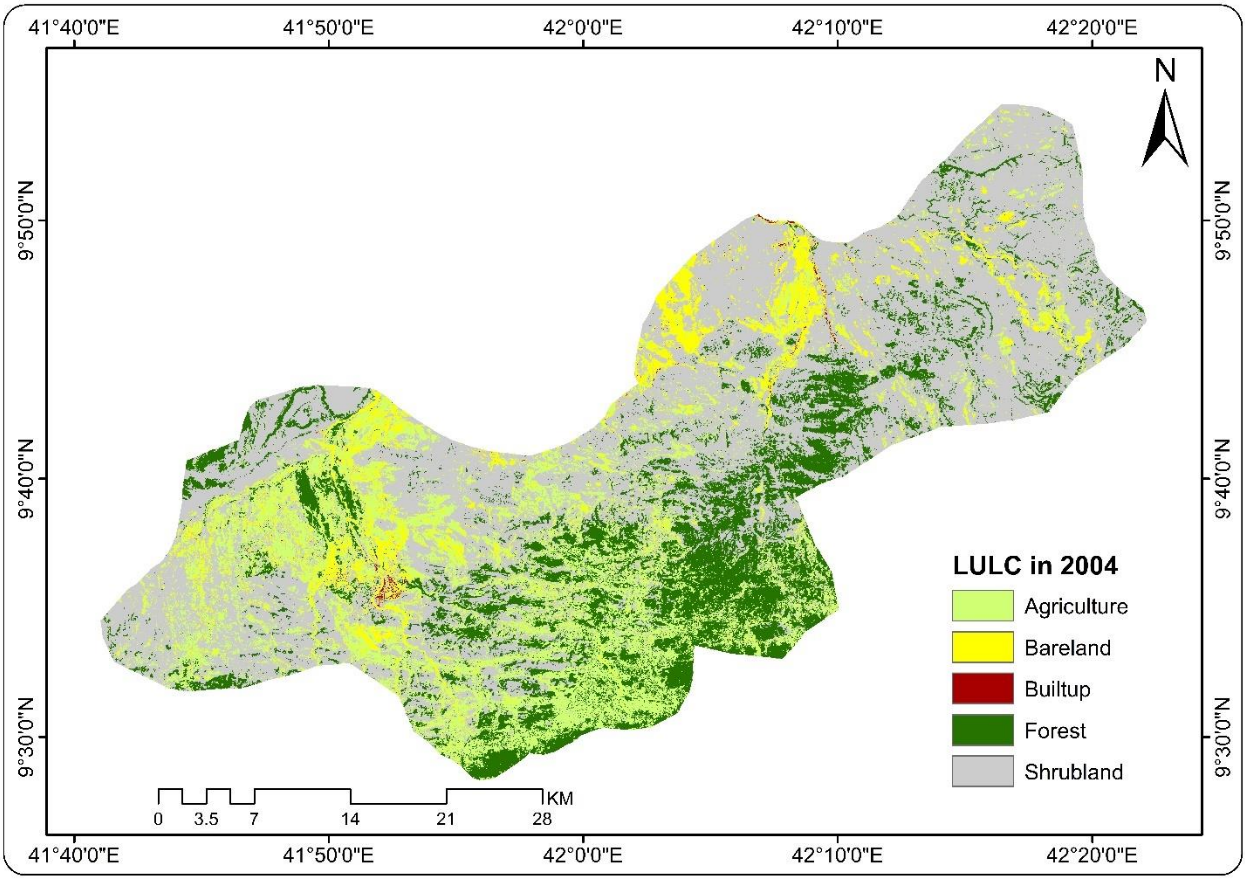


Figure 4-2: LULC in 2004

4.2.3. LULC in 2014

Urbanization was accelerated even further in 2014. Urban land increased even more dramatically to 1.48%, reflecting increasing residential, commercial areas, as well as especially informal settlements. Shrubland covered even larger portions of the landscape at 66.7%, largely the result of ongoing forest degradation and agricultural conversion of land. Forest cover reduced further to 10.4%, with issues regarding loss of biodiversity and decreasing accessibility of ecosystem services. Agricultural land reduced to 13%, which shows that urban and shrubland expansion was encroaching on arable land. Bareland remained unchanged at 8.3%, which reflects periodic but small unused land.

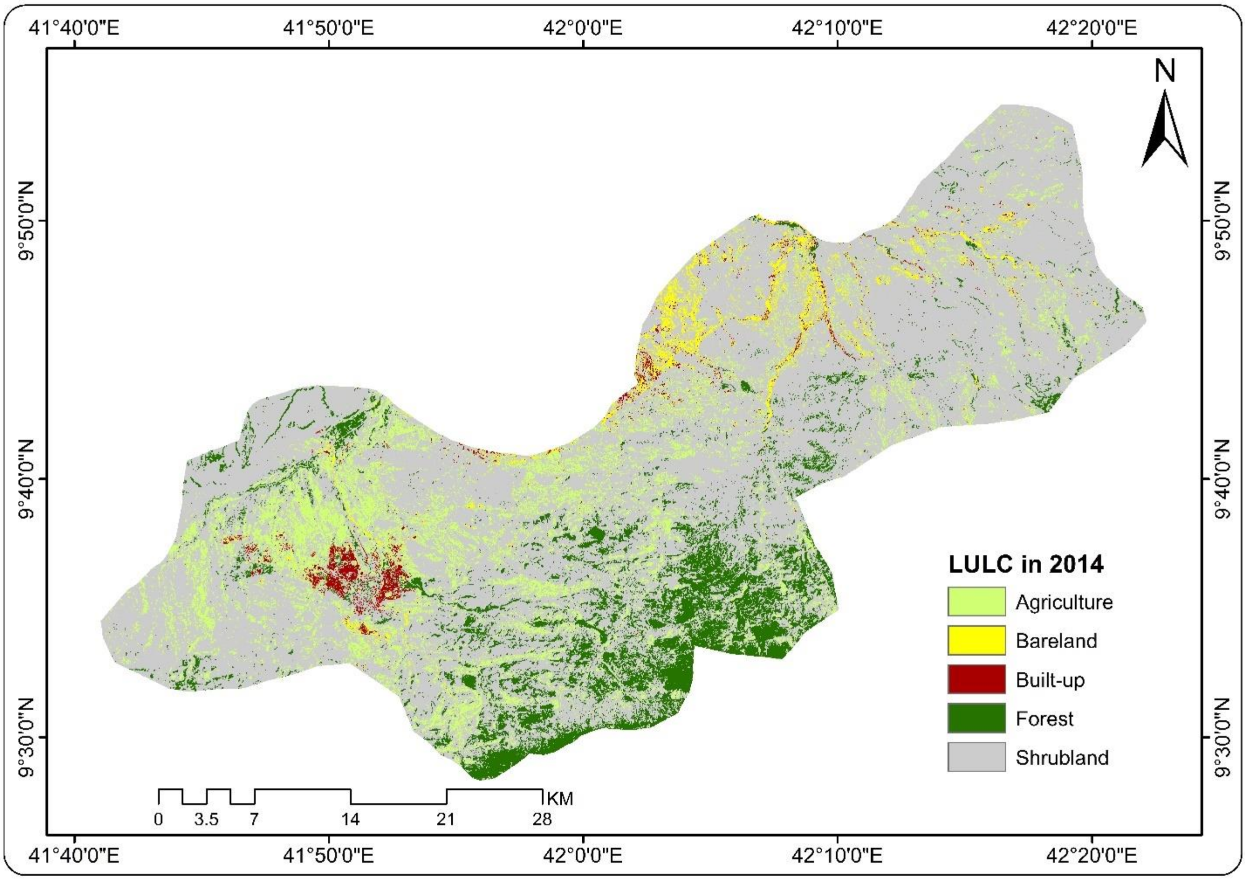


Figure 4-3: LULC in 2014

4.2.4. LULC in 2024

In 2024, the Land Use Land Cover (LULC) data for Dire Dewa City shows a landscape dominated by shrubland, which occupies 116,104.59 hectares or 75.61% of the total area, indicating widespread natural or semi-natural vegetation likely influenced by land abandonment, degradation, or limited agricultural activity. The built-up area, although only 2.20% of the total land (3377.19 ha), has seen a substantial increase from 0.07% in 1994, reflecting rapid urban expansion driven by population growth and infrastructural development. Agricultural land accounts for 15.14%, suggesting a moderate recovery from its decline in 2014, while forest cover has drastically decreased to 6.36%, highlighting ongoing deforestation pressures possibly due to urban and agricultural encroachment. Bareland has diminished to just 0.69%, indicating land conversion into other uses or vegetative recovery. These patterns illustrate the accelerating urbanization and shifting land dynamics typical of many rapidly growing cities in the Global South (Lambin et al., 2003; UN-Habitat, 2016).

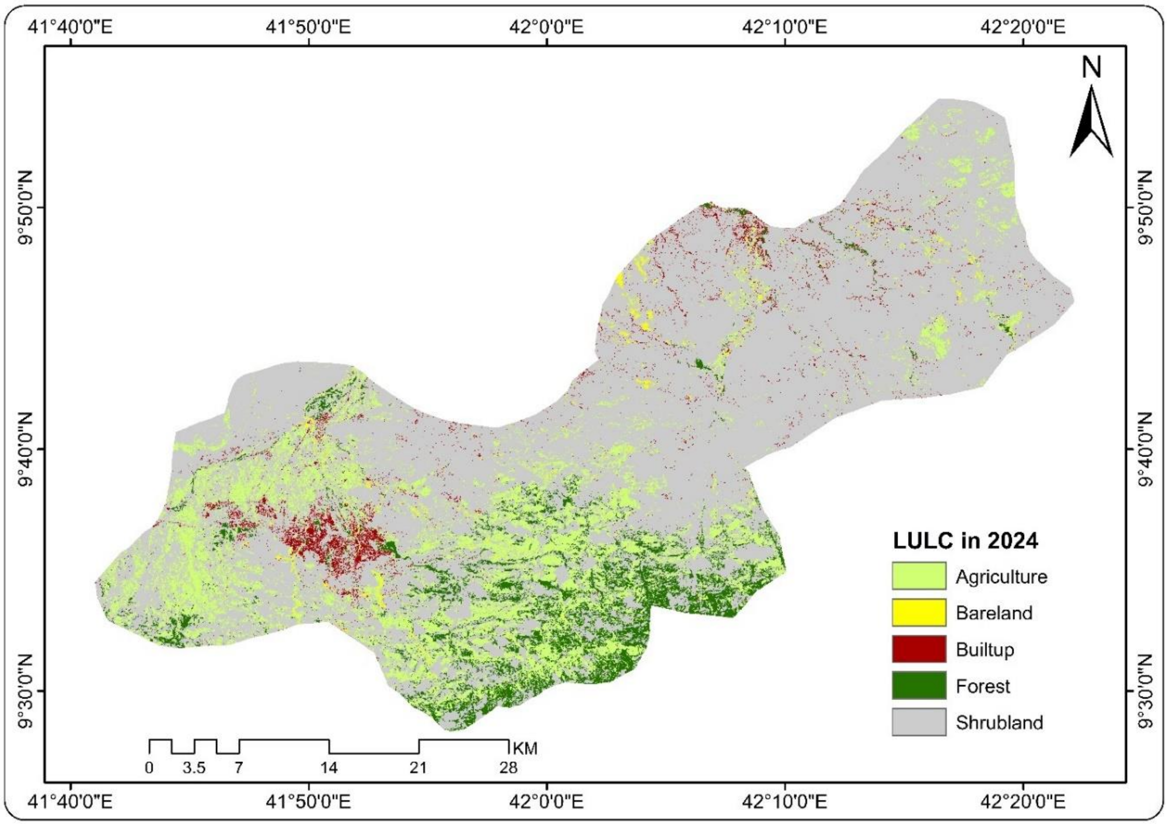


Figure 4-4: LULC in 2024

4.3.Change detection matrix

The change detection matrices provide a general snapshot of how land covers had evolved between specific periods, with gains, loss, and conversion among classes.

4.3.1. Change detection between 1994-2004

Forest cover declined significantly between 1994 and 2004 with only approximately 24,641 hectares remaining out of its initial 48,804 hectares, which means nearly half was converted, mainly into agricultural land and shrubland. Crop area improved considerably, mainly due to loss to agricultural land and shrubland, indicating rising cultivation activity. Built-up area, though still relatively small, started to grow, albeit marginally, showing trends of urbanization. Shrubland grew reasonably, mostly to the detriment of degraded forest as well as agriculture land. At large, positive times can be regarded as change periods when man pressure began restructuring the landscape.

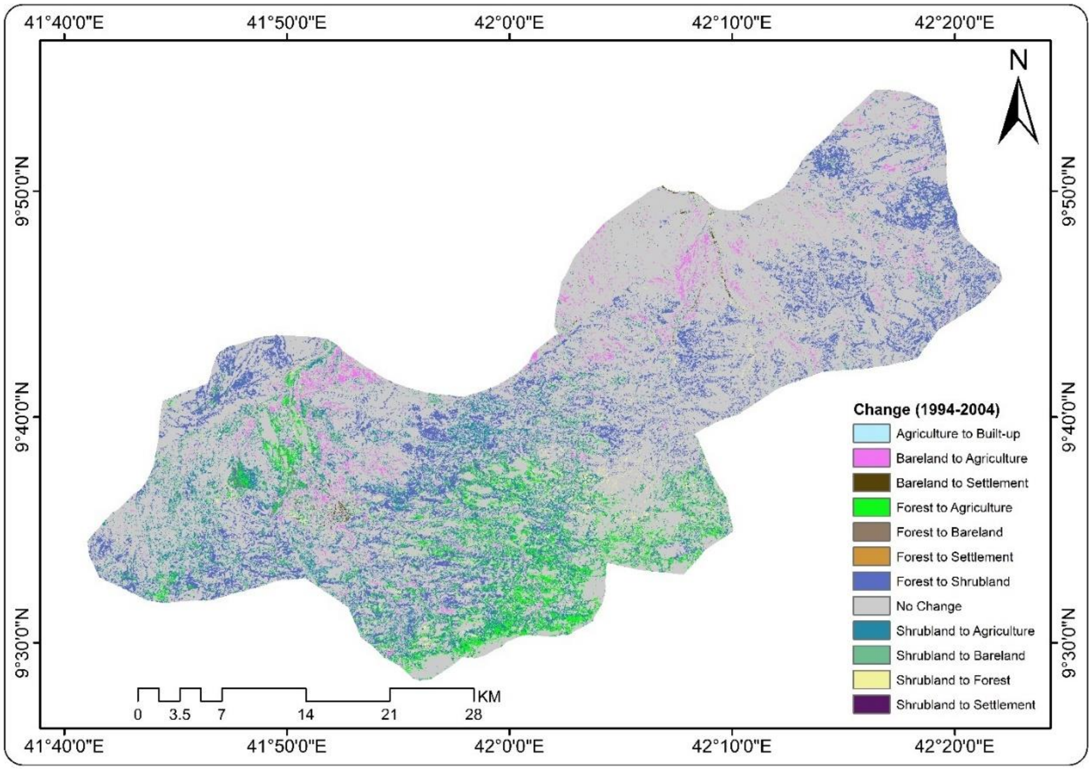


Figure 4-5: Change detection between 1994-2004

Table 4-2: Change detection matrix between 1994-2004

		2004					
		Agriculture	Bareland	Built-up	Forest	Shrubland	Grand Total
1994	Agriculture	7329.97	1355.77	3.90	327.46	2992.86	12009.97
	Bareland	3892.48	6893.17	141.39	66.45	1992.38	12985.87
	Built-up	0.37	40.57	43.66	0.06	12.72	97.39
	Forest	5727.52	135.33	2.41	24641.41	18297.86	48804.54
	Shrubland	11842.73	2394.36	46.72	2446.07	60030.41	76760.29
	Grand Total	28793.08	10819.19	238.08	27481.45	83326.25	150658.06

4.3.2. Change detection between 2004-2014

The period 2004-2014 saw land transformation at an unprecedented rate. Shrubland rose by far to over 74,799 hectares, predominantly through the loss of agriculture and forest land. Forest cover further declined, whereas agricultural land declined marginally owing to increasing pressure from shrubland and urbanization. Built-up area was the most dramatic to transform, from 238.21 hectares to 1,786.60 hectares, a monumental wave of informal settlement growth. Bareland also continued to reduce, typically degrading to shrubland or being utilized for agriculture or urban use.

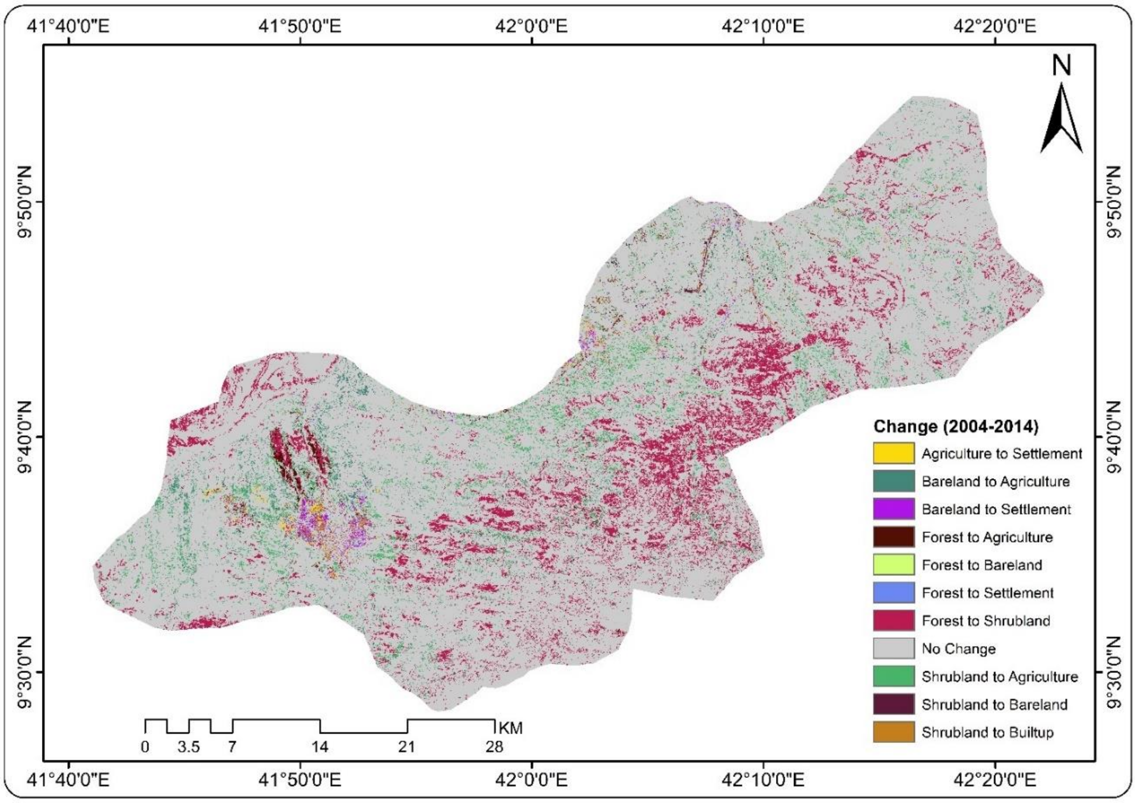


Figure 4-6: Change detection between 2004-2014

Table 4-3: Change detection matrix between 2004-2014

		LULC in 2014					
		Agriculture	Bareland	Built-up	Forest	Shrubland	Grand Total
LULC in 2004	Agriculture	9470.48	470.42	302.91	2548.11	16001.42	28793.34
	Bareland	2210.24	2284.59	630.72	139.76	5554.06	10819.36
	Built-up	2.22	88.84	120.10	0.36	26.70	238.21
	Forest	514.81	8.73	54.07	11669.96	15231.08	27478.66
	Shrubland	6143.76	729.46	678.81	981.25	74799.13	83332.41
	Grand Total	18341.51	3582.04	1786.60	15339.44	111612.38	150661.97

4.3.3. Change detection between 2014-2024

Between 2014 and 2024, the landscape continued to change toward human-dominated land use. Constructed land again expanded to an additional 2,947.15 hectares, showing continuous informal settlement spread. Shrubland continued to be the preponderant class, expanding across former agricultural, forest, and bareland classes. Forest cover decreased dramatically to leave remnant patches, whereas land devoted to agriculture continued to be under strain. Bareland all but disappeared as land was converted to more intensive uses. This most recent phase illustrates a cityscape engulfing all open space at the expense of environmental sustainability.

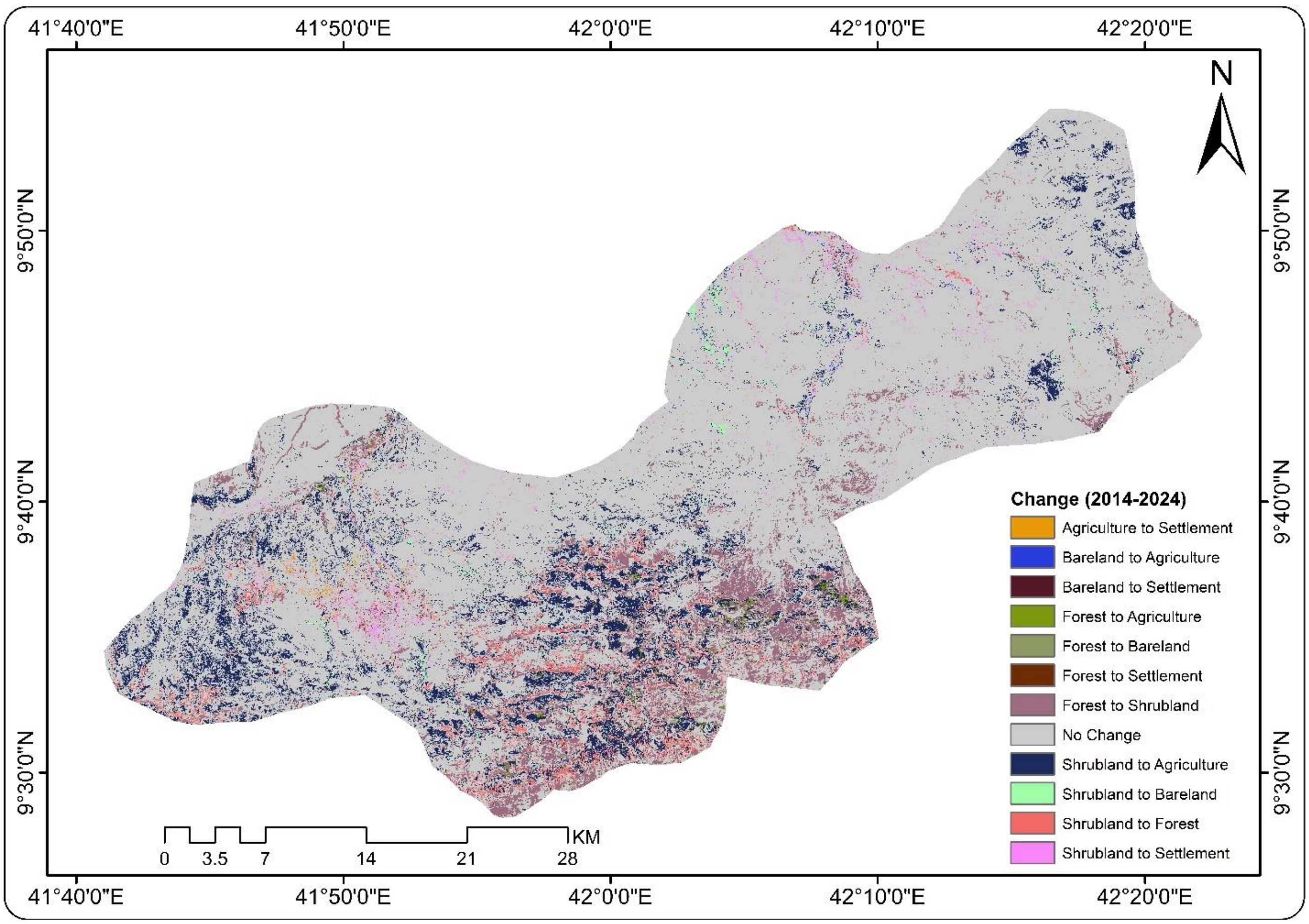


Figure 4-7: Change detection between 2014-2024

Table 4-4: Change detection matrix between 2014-2024

		LULC in 2024					
		Agriculture	Bareland	Built-up	Forest	Shrubland	Grand Total
LULC in 2014	Agriculture	6491.83	108.67	388.54	93.99	11258.52	18341.55
	Bareland	174.16	237.52	219.49	2.15	2948.55	3581.86
	Built-up	13.41	21.22	671.47	2.17	1078.28	1786.54
	Forest	635.22	1.33	84.09	5369.00	9247.49	15337.13
	Shrubland	14974.25	632.92	1583.57	3782.47	90640.26	111613.47
	Grand Total	22288.87	1001.66	2947.15	9249.77	115173.10	150660.55

4.3.4. Change detection between 1994-2024

Throughout the whole 30-year period, the land cover of Dire Dawa evolved significantly. Urbanized areas expanded over 30 times, from 97 hectares in 1994 to nearly 2,947.15 hectares in 2024, led mainly by the expansion of slums. Forest cover suffered immense loss, decreasing by nearly 75%, largely being replaced by shrubland and parts of agricultural land. Shrubland became the dominating land use, expanding over former forest areas, agricultural fields, and barelands. Cropland experienced the opposite, having both decreasing and then increasing trends with the urbanization pressures as well as the pressure from the shrublands. The trends show increased environmental degradation, increased human pressure, and higher urban demands on land resources that are scarce.

Table 4-5: Change detection matrix between 1994-2024

		LULC in 2024					
		Agriculture	Bareland	Built-up	Forest	Shrubland	Grand Total
LULC in 1994	Agriculture	5043.75	60.31	299.47	357.01	6249.76	12010.30
	Bareland	1951.44	768.45	723.28	110.01	9432.82	12986.00
	Built-up	0.98	2.81	36.06	0.12	57.29	97.25
	Forest	4009.77	27.03	310.67	6543.21	37916.62	48807.30
	Shrubland	11283.40	143.20	1577.07	2239.42	61513.73	76756.82
	Grand Total	22289.33	1001.81	2946.54	9249.78	115170.22	150657.68

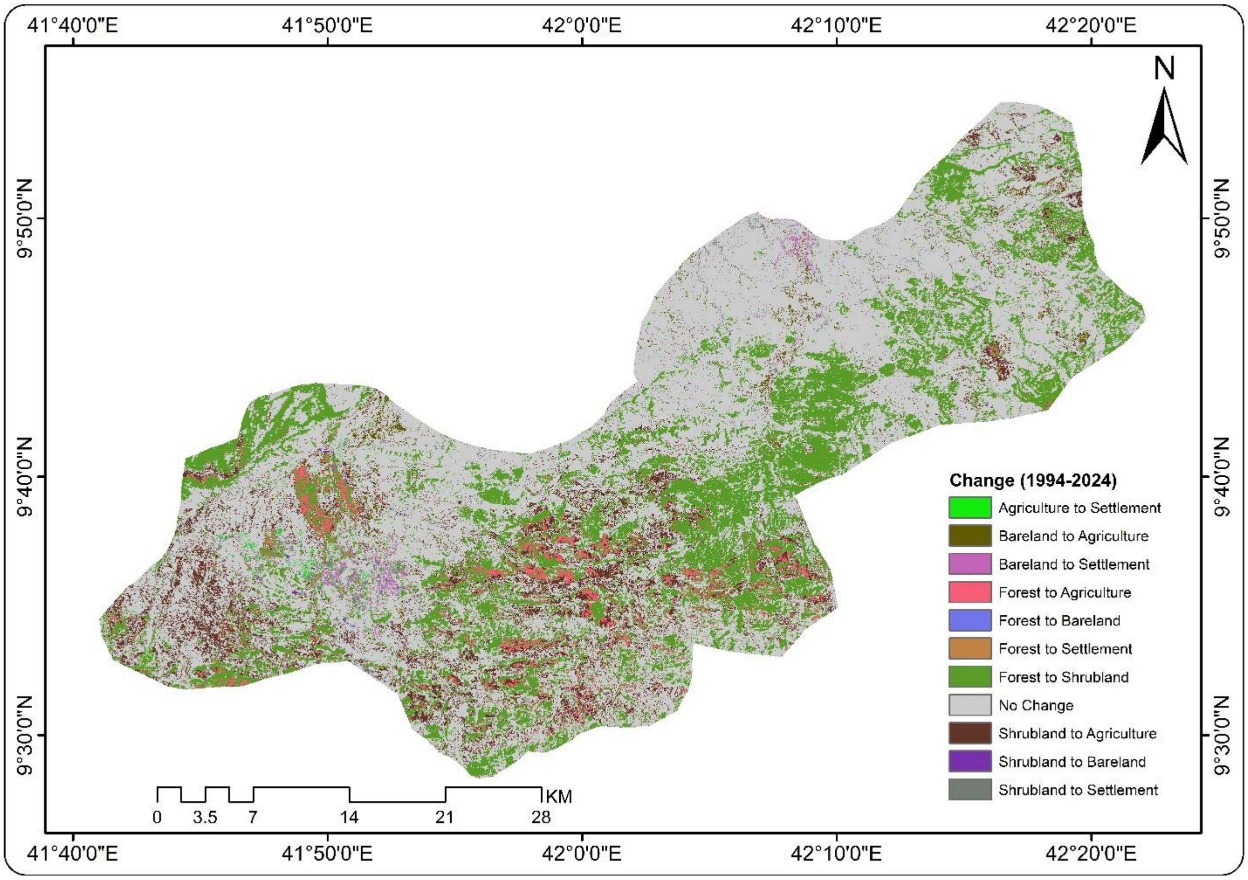


Figure 4-8: Change detection between 1994-2024

4.4.Accuracy assessments of LULC classification results

Accuracy assessment was performed to ensure the credibility and reliability of the classified maps used in the analysis. This section presents the overall accuracy (OA), kappa coefficient, producer's accuracy (PA), and user's accuracy (UA) for each year's classification.

4.4.1. Accuracy assessment result for 1994 classification

The 1994 classification achieved an overall accuracy (OA) of 84% with a kappa coefficient of 0.80, indicating a high agreement between the classified map and reference data. Specifically, the built-up class showed a producer's accuracy (PA) of 85.19% and a user's accuracy (UA) of 79.31%. Agriculture had a PA of 90.00% and UA of 81.82%, forest had 82.00% PA and 87.23% UA, shrubland had 79.63% PA and 87.76% UA, and bareland had 84.21% PA and 85.71% UA. Minor misclassifications were observed mainly between shrubland and agriculture, reflecting their spectral similarity.

Table 4-6: Accuracy assessment result for 1994 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	46	2	0	2	4	54	85.19
Agriculture	1	45	2	1	1	50	90.00
Forest	4	1	41	1	3	50	82.00
Shrubland	3	5	3	43	0	54	79.63
Bareland	4	2	1	2	48	57	84.21
Total	58	55	47	49	56	265	
UA	79.31	81.82	87.23	87.76	85.71		
OA	0.84						
Kappa	0.80						

4.4.2. Accuracy assessment result for 2004 classification

The 2004 classification showed improved accuracy with an OA of 86% and a kappa coefficient of 0.83. Built-up land recorded a PA of 90.00% and UA of 78.95%; agriculture, 83.93% PA and 83.93% UA; forest, 86.54% PA and 91.84% UA; shrubland, 85.19% PA and 86.79% UA; and bareland, 84.91% PA and 90.00% UA. While agricultural and forest areas were well mapped, some confusion persisted in distinguishing shrubland due to the presence of mixed vegetation.

Table 4-7: Accuracy assessment result for 2004 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	45	2	0	2	1	50	90.00
Agriculture	4	47	2	2	1	56	83.93
Forest	2	1	45	1	3	52	86.54
Shrubland	3	4	1	46	0	54	85.19
Bareland	3	2	1	2	45	53	84.91
Total	57	56	49	53	50	265	
UA	78.95	83.93	91.84	86.79	90.00		
OA	0.86						
Kappa	0.83						

4.4.3. Accuracy assessment result for 2014 classification

The 2014 classification achieved an OA of 85% and a kappa coefficient of 0.82. The built-up class showed a PA of 87.50% and UA of 89.09%; agriculture, 89.80% PA and 80.00% UA; forest, 84.91% PA and 83.33% UA; shrubland, 79.25% PA and 85.71% UA; and bareland, 85.19% PA and 88.46% UA. Urban areas were better classified due to stronger land use signals, though some intermixing between shrubland and cropland remained.

Table 4-8: Accuracy assessment result for 2014 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	49	2	0	3	2	56	87.50
Agriculture	2	44	2	0	1	49	89.80
Forest	2	1	45	2	3	53	84.91
Shrubland	2	6	3	42	0	53	79.25
Bareland	0	2	4	2	46	54	85.19
Total	55	55	54	49	52	265	
UA	89.09	80.00	83.33	85.71	88.46		
OA	0.85						
Kappa	0.82						

Table 4-9: Accuracy assessment result for 2024 classification

	Built-up	Agriculture	Forest	Shrubland	Bareland	Total	PA
Built-up	43	2	4	2	1	52	82.69
Agriculture	6	46	2	3	1	58	79.31
Forest	2	1	45	1	3	52	86.54
Shrubland	1	4	3	44	2	54	81.48
Bareland	0	2	2	2	43	49	87.76
Total	52	55	56	52	50	265	
UA	82.69	83.64	80.36	84.62	86.00		
OA	0.83						
Kappa	0.79						

4.4.1. Accuracy assessment result for 2024 classification

The 2024 classification, estimated as the most accurate, reached an OA of 83% and a kappa coefficient of 0.79. The built-up class showed 82.69% PA and 82.69% UA; agriculture, 79.31% PA and 83.64% UA; forest, 86.54% PA and 80.36% UA; shrubland, 81.48% PA and 84.62% UA; and bareland, 87.76% PA and 86.00% UA.

4.5.Landscape metrices for informal settlement detection

4.5.1. Edge density

The temporal analysis of edge density across the eight urban zones from 1994 to 2024 reveals a compelling narrative of urban growth, spatial transformation, and the emergence of informal settlements. Edge density, defined as the total length of edge per unit area, is a critical landscape metric for evaluating fragmentation and the complexity of urban morphology (McGarigal & Marks, 1995). In an urban context, increasing edge density is often associated with irregular development patterns, such as the spread of informal settlements, urban sprawl, and the subdivision of land into smaller, disorganized units.

Between 1994 and 2024, all eight zones exhibited a significant increase in edge density, indicating a marked rise in landscape fragmentation. This pattern is particularly evident in Zones 1, 6, 7, and 8, which show sharp increases from relatively low initial values. For instance, Zone 8 surged from 13.21 to 70.12, marking the highest absolute increase among all zones (Figure 4-11). Such dramatic growth is symptomatic of rapid and unplanned urban expansion, likely characterized by irregular plot shapes, inadequate infrastructure, and a lack of planning controls hallmarks of informal settlements (Kuffer, Barros & Sliuzas, 2014). These findings are consistent with the literature, which identifies high edge density as a spatial signature of informal areas due to the fragmentation caused by self-built, unregulated structures (Taubenböck et al., 2012).

Zones 1 and 6 also show significant jumps in edge density, particularly after 2004, suggesting a phase of rapid spatial change. This aligns with studies by Herold et al. (2005), who emphasized that peri-urban areas often experience the most intense landscape restructuring due to informal and semi-formal expansion. The acceleration of edge density in these zones implies increasing subdivision of land, possibly driven by population pressure, rural-to-urban migration, and the inability of formal planning mechanisms to accommodate the urban poor (UN-Habitat, 2003). This pattern of growth results in complex, irregular settlement footprints that elevate the edge-to-area ratio of built-up patches.

Conversely, Zones 3 and 4 showed more moderate increases in edge density, suggesting relatively stable and possibly formalized development. Zone 4, for example, already had a higher starting point in 1994 (11.23) and grew steadily to 33.12 in 2024. This may reflect planned densification or controlled infill within a regulated urban framework. Planned areas typically maintain geometric regularity and lower fragmentation, resulting in slower increases in edge density over time (Jat et al., 2008). The differences in edge density trajectories between these zones underscore the heterogeneity of urban growth patterns and the coexistence of formal and informal processes within the same cityscape.

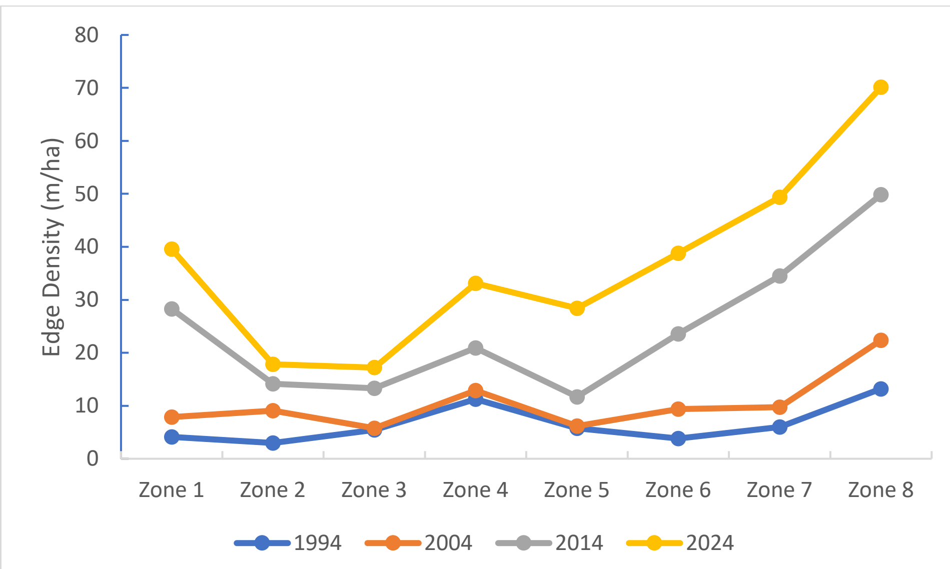


Figure 4-9: Edge density (ED)

4.5.2. Largest Patch Index (LPI)

The Largest Patch Index (LPI) measures the dominance of the largest built-up patch in each zone as a percentage of the total area. In urban studies, a higher LPI indicates spatial consolidation of the built environment, often associated with formalization and urban intensification. Conversely, a lower LPI reflects fragmented landscapes, frequently characteristic of early-stage or persistent informal settlements (Li et al., 2020; Zhang et al., 2022).

Zone 1 and Zone 8 experienced the most prominent LPI increases from 0.85% to 7.75% and 2.1% to 9.98% respectively (Figure 4-12). This strong upward trend signals dominant patch emergence, likely representing the maturation of informal clusters into dense, coalesced urban areas. According to Mahabir et al. (2016), such transitions are common in fringe areas of Global South cities, where informal settlements expand rapidly and later densify into consolidated patches due to population pressure and lack of land regulation.

These zones also align with high edge density and low compactness observed in your prior results, further supporting the identification of unplanned urban expansion (Jain et al., 2021). Zone 6 and Zone 7 showed strong but slightly slower LPI increases, ending at 2.89% and 6.89%, respectively. This pattern is typical of densifying informal zones where scattered small patches begin to merge over time, especially in response to informal land markets or political tolerance (Kohli et al., 2012). Their spatial evolution suggests mid-level patch cohesion with potentially high population density, often associated with vulnerable informal settlements (Benz & Kohli, 2019).

Zones 2 and 4 reached 2.67% and 1.55% respectively in 2024. While these values represent growth from 1994, they are relatively low compared to Zones 1 and 8. The fluctuations and slower consolidation here could be linked to planned interventions, zoning restrictions, or natural boundaries inhibiting unregulated expansion (Liu et al., 2017). Such areas reflect a hybrid urban form semi-formal developments where informal structures coexist with regulated expansion.

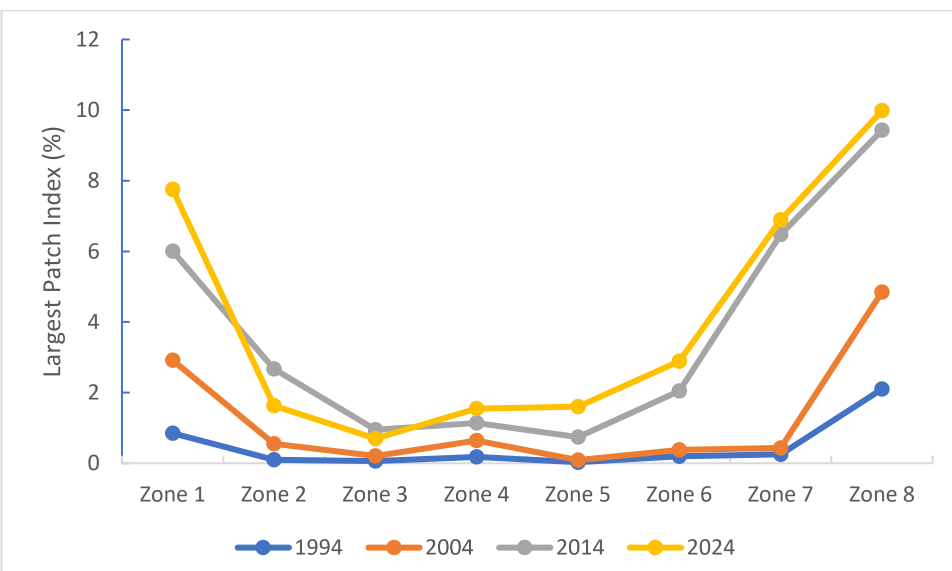


Figure 4-10: Largest Patch Index (LPI)

4.5.3. Fractal Dimension Index (FDI)

The Fractal Dimension Index (FDI) is a well-established spatial metric used to quantify the complexity of urban forms, particularly effective in distinguishing between formal and informal settlement patterns. The values in this analysis range from approximately 1.04 to 1.37 over a 30-year period (1994–2024) across eight urban zones. A general upward trend in FDI across all zones is evident, indicating an overall increase in the morphological complexity of urban areas.

Zone 8 emerges as the most dynamically evolving zone, with the FDI increasing from 1.15 in 1994 to 1.37 in 2024. This substantial rise reflects a growing irregularity and complexity in built-up patch shapes, suggesting a pattern of rapid, informal, and unplanned urban growth. According to Kuffer et al. (2016), informal settlements often exhibit higher FDI values due to their unregulated spatial development, irregular building alignments, and lack of urban planning.

Zones 7 and 1 follow similar trajectories, recording significant FDI growth (from 1.09 to 1.30 and 1.12 to 1.28, respectively). These patterns support the interpretation that these zones are undergoing intensive morphological transformation, typical of densifying informal settlements. Informal settlements tend to evolve over time, not just through horizontal expansion, but also through internal densification and subdivision of plots, which further increases boundary complexity (Herold et al., 2003).

Zones 6 and 4 display moderate FDI increases (from 1.08 to 1.24 and 1.10 to 1.20, respectively), reflecting intermediate stages of informal settlement formation. These zones likely represent semi-informal neighborhoods or transition areas where planning controls are either relaxed or inconsistently enforced. Literature such as Bhatta (2010) suggests that these zones undergoing progressive informalization, where land tenure is ambiguous and planning is reactive rather than proactive.

Conversely, Zones 2 and 3 exhibit relatively stable FDI values, with Zone 3 showing the lowest overall increase (from 1.04 to 1.10). Such limited growth in spatial complexity suggests these zones are likely formally planned or spatially constrained, maintaining more regular urban shapes. According to Mahabir et al. (2016), lower FDI values are associated with areas where urban expansion is regulated, land use is compartmentalized, and infrastructure networks are systematically designed.

Zone 5, although showing a smaller increase (from 1.05 to 1.19), may represent a newly developing fringe area where informal settlement is starting to emerge. The gradual increase in FDI suggests recent construction activity that lacks spatial order but hasn't yet reached the complexity observed in more mature informal areas like Zones 7 and 8.

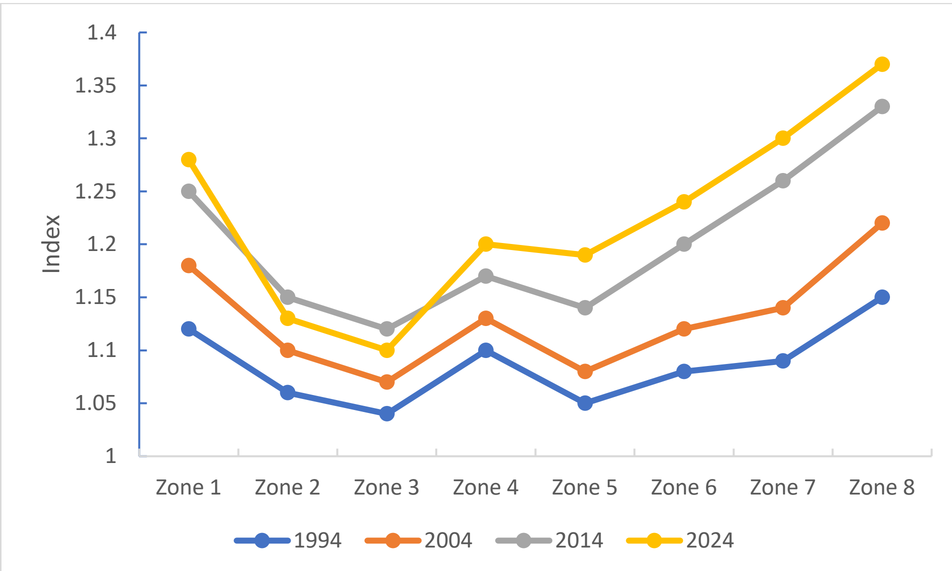


Figure 4-11: Fractal Dimension Index (FDI)

4.5.4. Euclidean Nearest Neighbor (ENN)

Over time, the data shows a steady increase in the values across all zones, which likely indicates the growth of informal settlements. Zone 3, in particular, exhibits the most rapid growth, from 205 in 1994 to 275 in 2024, making it a focal point of interest. This kind of growth aligns with urbanization trends observed in many global cities, where informal settlements tend to form in response to both migration and economic pressures, often growing in proximity to existing urban areas (UN-Habitat, 2016). The steady increase in Zone 5 (from 185.3 in 1994 to 265.6 in 2024) suggests that it, too, is experiencing significant growth, likely driven by similar factors such as economic opportunities, infrastructure development, or land availability.

Conversely, Zone 8 shows the slowest growth, with values increasing from 76.9 in 1994 to 110.2 in 2024. This could suggest that Zone 8 is either more isolated or less desirable for settlement expansion, possibly due to distance from key infrastructure or economic hubs. In many cities, informal settlements often form along transportation corridors or in areas close to employment centers (Satterthwaite, 2014). The slower growth in Zone 8 could indicate that it is further from these drivers of settlement growth.

The Euclidean Nearest Neighbor (ENN) method can be applied to measure the spatial distribution of informal settlements over time. ENN calculates the straight-line distance from a given point to its nearest neighbor, providing insights into whether settlements are clustering together or spreading out. Informal settlements tend to exhibit patterns of spatial clustering (Angel et al., 2011), where people are often pushed into close proximity due to the lack of available land, proximity to jobs, or affordable housing options. In the context of the provided data, the rapid growth in Zone 3 may indicate a cluster forming in this zone, likely driven by its proximity to formalized urban areas or services.

As settlements grow, especially in rapidly urbanizing regions, the ENN can reveal how different zones are related spatially. If settlements in Zone 3 are indeed clustering together, it would suggest that this zone is becoming a focal point for informal development, possibly driven by its proximity to existing infrastructure or more central urban areas. Informal settlements often emerge in the peri-urban areas, which are characterized by limited access to services and infrastructure, yet their proximity to urban centers makes them desirable for those seeking cheaper living spaces (Turok & McGranahan, 2013). The ENN could highlight whether Zone 3 is developing along key transport corridors or near urban centers, reinforcing the idea that informal settlements often grow where access to infrastructure is still limited but close to existing urban spaces.

On the other hand, the slow growth in Zone 8 suggests potential isolation from urban infrastructure. Informal settlements that are isolated or distant from essential services such as schools, healthcare, and transportation networks often face greater challenges in terms of development (Mukhija, 2004). Using ENN, one could calculate the proximity of Zone 8 to central urban areas or existing formal settlements. If the ENN analysis reveals that Zone 8 is farther from urbanized areas, it would support the hypothesis that isolation is a key factor limiting growth in this region.

The relationship between the proximity of informal settlements to infrastructure and their growth is well-documented. Urban planning literature shows that settlements tend to form in areas with easier access to basic services, but also in locations where land is cheaper or informally available (Satterthwaite, 2014). If Zone 8 is found to be further away from critical services or infrastructure, it could indicate that the lack of access to these services is a limiting factor for informal settlement growth.

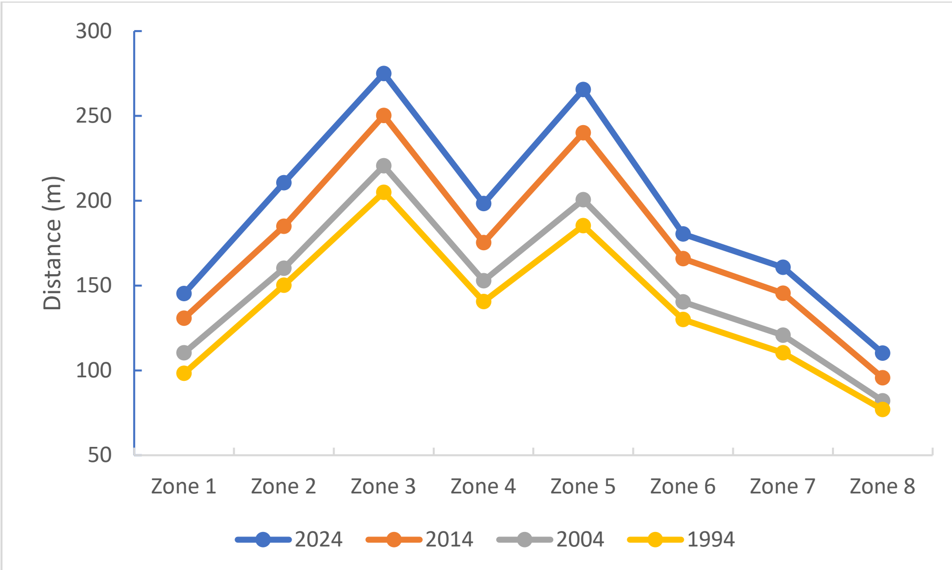


Figure 4-12: Euclidean Nearest Neighbor (ENN)

4.5.5. Informal settlement determination using spatial metrices

4.5.6. Compactness (m^2)

Figure 4-13 reveals the spatial distribution of compactness in urban areas, classified into four levels: Very Low, Low, High, and Very High compactness, expressed in square meters (m^2). Compactness here likely refers to a shape-based metric that evaluates how geometrically efficient or "regular" each built-up patch is lower values typically indicate irregular, fragmented, or elongated shapes, while higher values are associated with more compact, circular, or square-like geometries. In urban morphology, compactness is a useful proxy for distinguishing between formal and informal settlements, as the two exhibit vastly different development patterns, planning regulations, and land use logic.

Upon examining the spatial patterns in the upper panels of the figure, areas with Very Low to Low compactness (highlighted in red and purple) are predominantly located on the urban periphery and are distinctly separated from the more compact and cohesive urban core, which is shown in light green and blue colors (high and very high compactness, respectively). The informal settlement areas, outlined in blue squares, correspond largely to the low-compactness zones, whereas formal settlements, delineated in green, coincide with regions of high or very high compactness. This observation is consistent with the spatial logic of urban growth in many developing cities, where informal settlements often emerge in marginal lands such as steep slopes, peri-urban zones, or lands lacking legal status or planning control (UN-Habitat, 2003).

In the lower panels of the image, which provide high-resolution RGB validation imagery from two selected sites (labeled a and b), the structural differences between informal and formal settlements become strikingly clear. In Site (a), the informal area (blue box) exhibits irregular building layouts, non-uniform plot sizes, and sparse land use, with many gaps and unplanned pathways. This corresponds to the very low compactness values in the raster above. In contrast, the formal area (green box) shows a regular grid of closely packed structures, reflecting a more organized urban design and higher compactness index. A similar pattern is observed in Site (b): the formal settlement appears denser and spatially cohesive, while the informal zone is patchy, disordered, and less spatially efficient.

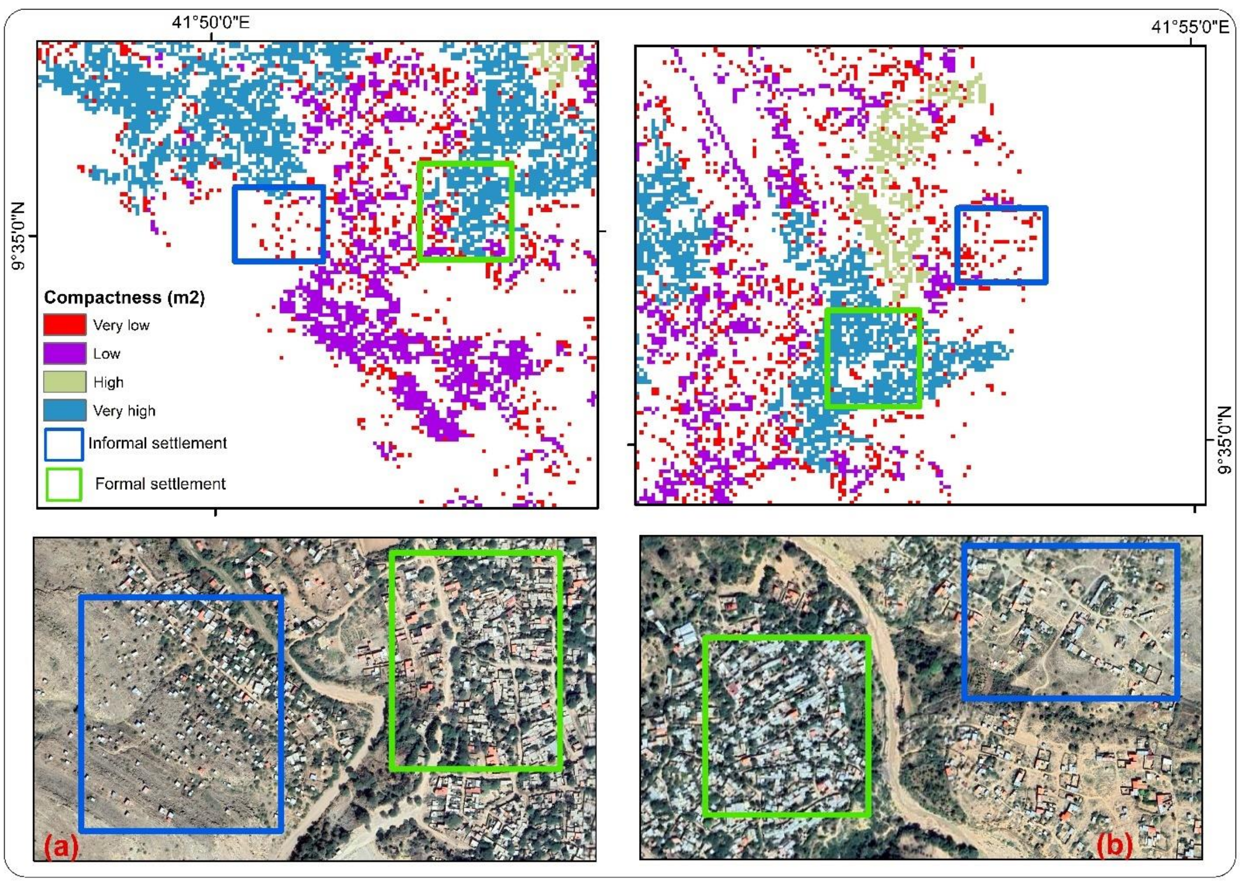


Figure 4-13: Informal settlement indicators based on Compactness values of patches and validation against high Resolution RGB SAS planet data (a) Site 1 and (b) Site 2

These findings are supported by a growing body of literature that utilizes spatial metrics and remote sensing to identify informal urbanization. For example, Taubenböck et al. (2012) and Kuffer et al. (2016) demonstrated that spatial metrics such as compactness, edge density, and shape index could differentiate formal from informal areas with high accuracy. Informal settlements tend to have lower compactness, higher shape complexity, and greater spatial dispersion, all of which are quantifiable through morphological analysis.

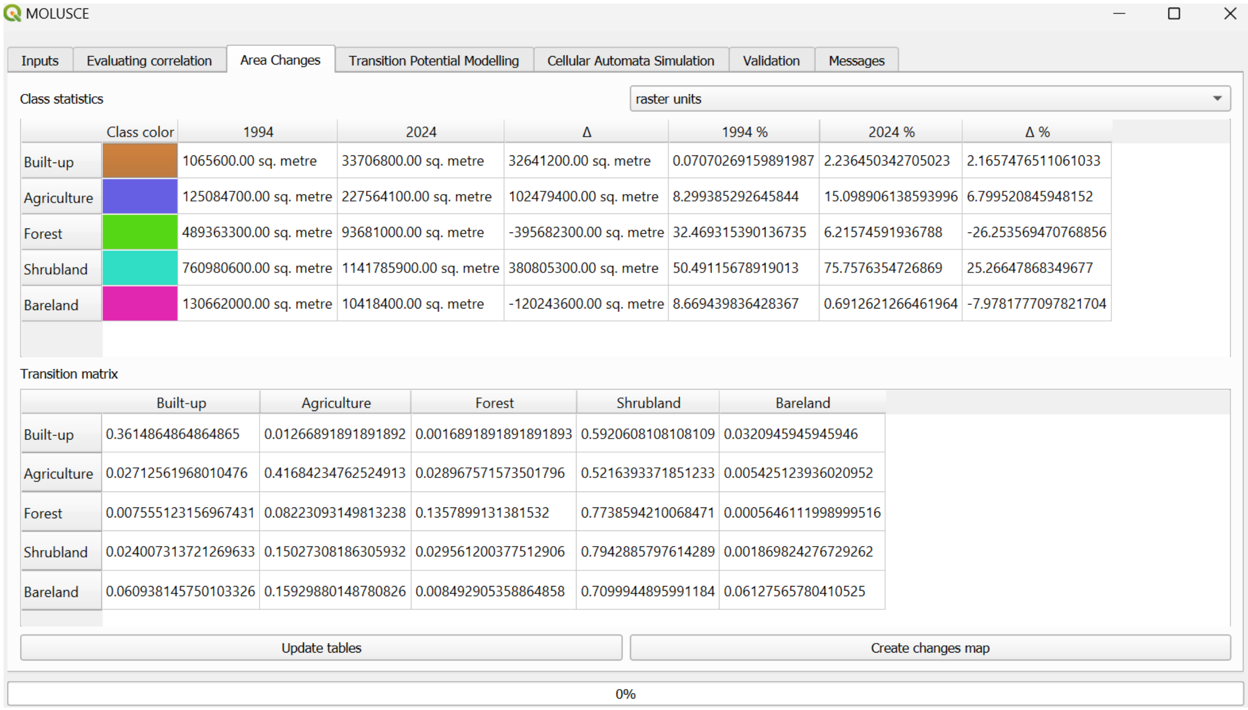
4.6.Simulations using CA-Markov model

The Cellular Automata (CA)-Markov model simulation results in MOLUSCE provide a detailed picture of land use and land cover (LULC) transitions in Dire Dewa between 1994 and 2024. According to the class statistics, the most prominent change is observed in shrubland, which expanded from approximately 76,098,000 sq. meters (50.49%) in 1994 to 114,175,800 sq. meters (75.76%) in 2024, a gain of over 38 million sq. meters. This suggests significant land conversion into shrubland, possibly from previously cultivated or forested areas, aligning with trends of land degradation or abandonment noted in similar semi-arid urban peripheries (Lambin et al., 2003).

Conversely, forest cover sharply declined from 48,936,300 sq. meters (32.46%) to 9,368,100 sq. meters (6.22%), a loss of approximately 39.6 million sq. meters, reflecting a −26.23% change. This supports concerns about deforestation due to expanding urban and agricultural areas. Built-up areas increased substantially from 1,065,600 sq. meters (0.07%) to 3,370,680 sq. meters (2.24%), reflecting urban growth driven by population pressure and infrastructure development. This aligns with studies on rapid urban expansion in secondary cities across the Global South (UN-Habitat, 2020).

Agricultural land also saw a significant increase of 10.27 million sq. meters, rising from 8.29% to 15.09% of the total area. This rebounds, despite forest loss, may indicate intensification or reallocation of land to farming, possibly influenced by economic shifts or food security initiatives. Meanwhile, bareland decreased significantly (12 million sq. meters), declining from 8.66% to just 0.61%, suggesting reclamation or vegetation regrowth in previously barren zones.

The transition matrix further supports these changes: a notable proportion of forest (13.57%) and bareland (15.93%) converted into shrubland, while agricultural land transitioned into both shrubland (27.49%) and built-up areas (2.71%).



	Class color	1994	2024	Δ	1994 %	2024 %	Δ %
Built-up		1065600.00 sq. metre	33706800.00 sq. metre	32641200.00 sq. metre	0.07070269159891987	2.236450342705023	2.1657476511061033
Agriculture		125084700.00 sq. metre	227564100.00 sq. metre	102479400.00 sq. metre	8.299385292645844	15.098906138593996	6.799520845948152
Forest		489363300.00 sq. metre	93681000.00 sq. metre	-395682300.00 sq. metre	32.469315390136735	6.21574591936788	-26.253569470768856
Shrubland		760980600.00 sq. metre	1141785900.00 sq. metre	380805300.00 sq. metre	50.49115678919013	75.7576354726869	25.26647868349677
Bareland		130662000.00 sq. metre	10418400.00 sq. metre	-120243600.00 sq. metre	8.669439836428367	0.6912621266461964	-7.9781777097821704

Transition matrix

	Built-up	Agriculture	Forest	Shrubland	Bareland
Built-up	0.3614864864864865	0.01266891891891892	0.0016891891891891893	0.5920608108108109	0.0320945945945946
Agriculture	0.02712561968010476	0.41684234762524913	0.028967571573501796	0.5216393371851233	0.005425123936020952
Forest	0.007555123156967431	0.08223093149813238	0.1357899131381532	0.7738594210068471	0.0005646111998999516
Shrubland	0.024007313721269633	0.15027308186305932	0.029561200377512906	0.7942885797614289	0.001869824276729262
Bareland	0.060938145750103326	0.15929880148780826	0.008492905358864858	0.7099944895991184	0.06127565780410525

Figure 4-14: Area change determination for future scenario simulation in MOLUSCE tool

4.6.1. Transition potential modelling

The neural network learning curve shown in the Figure (4-15) demonstrates the training and validation performance over 1,000 epochs for the transition potential modeling stage of a CA-Markov (Cellular Automata–Markov) model used to simulate future land use/land cover (LULC) changes, specifically for Dire Dawa City by the year 2054.

At the beginning of training, both training and validation losses are relatively high, indicating that the model starts with a poor fit. However, a sharp decline in both losses is observed within the first 100 epochs, suggesting rapid learning and adjustment of the model parameters during this initial phase. The green dots represent training loss, which shows a smooth and consistent decline, stabilizing around a very low value (~0.05) after approximately 150 epochs. This indicates that the model effectively learned the patterns from the training dataset with minimal error.

On the other hand, the red line representing validation loss exhibits higher variability and noise throughout the training process. Despite this fluctuation, the overall trend also shows a gradual decline and convergence close to the training loss after several hundred epochs, especially beyond 300 epochs. This convergence and relatively stable gap between training and validation losses suggest that the model generalizes well to unseen data and is not overfitting.

In the context of CA-Markov modeling for LULC simulations, this neural network likely served as a suitability or transition potential model to identify the likelihood of land use transitions based on spatial variables. The effective training demonstrated in this learning curve provides confidence in the model's predictive capabilities for generating accurate LULC scenarios for 2054. Therefore, the transition potential map produced from this well-trained model would be a reliable input for simulating future land cover dynamics in Dire Dawa City under the CA-Markov framework.

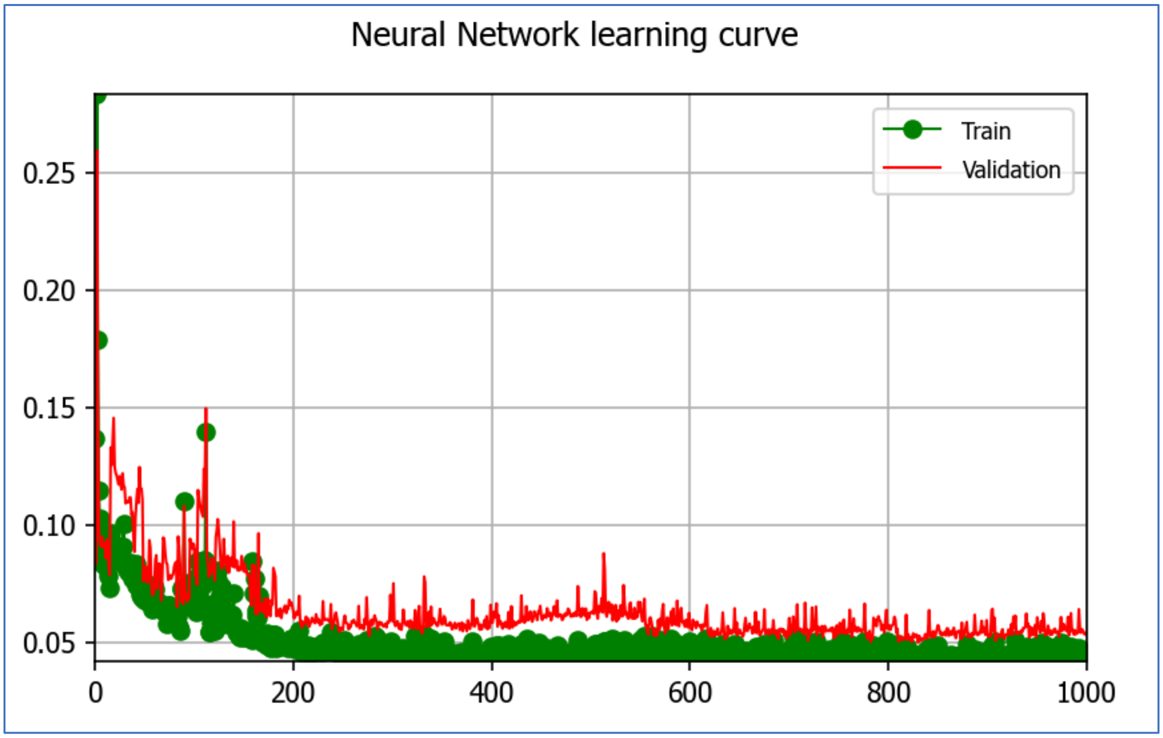


Figure 4-15: Model training and validation using ANN curve

4.6.2. Cellular Automata (CA) simulation for 2054

The LULC simulation results for Dire Dawa City in 2054, based on the CA-Markov model, reveal substantial land cover changes when compared to the 2024 baseline. From the table, built-up areas are projected to significantly increase from 3,377.19 ha (2.20%) in 2024 to 10,563.97 ha (6.88%) by 2054. This nearly threefold increase in urban land suggests rapid urbanization and population growth, which is consistent with urban development trends in many Ethiopian cities.

Agricultural land shows the most dramatic rise, increasing from 23,241.20 ha (15.14%) to 59,792.24 ha (38.94%). This sharp expansion reflects a growing demand for food and livelihood dependence on farming, likely driven by demographic pressure and possibly improved agricultural policies or land conversion from shrubland and forest areas.

Conversely, shrubland experiences a severe decline from 116,104.59 ha (75.61%) in 2024 to 60,022.90 ha (39.09%) in 2054. This reduction of more than 56,000 ha underscores the pressure exerted by agricultural expansion and settlement growth, suggesting degradation of natural vegetation and potential ecological imbalance.

Forest areas also show a modest increase, from 9,764.43 ha (6.36%) to 16,514.62 ha (10.76%). This might indicate reforestation or afforestation initiatives, or a reclassification of dense vegetation due to land recovery processes. Nonetheless, given the broader trends, it is also possible that some shrubland areas transitioned into forest through natural succession or land management efforts. Lastly, bareland grows from 1,060.14 ha (0.69%) to 6,653.79 ha (4.33%). This could be a result of land degradation, deforestation, or over-exploitation of agricultural lands leading to soil exposure and loss of vegetation cover.

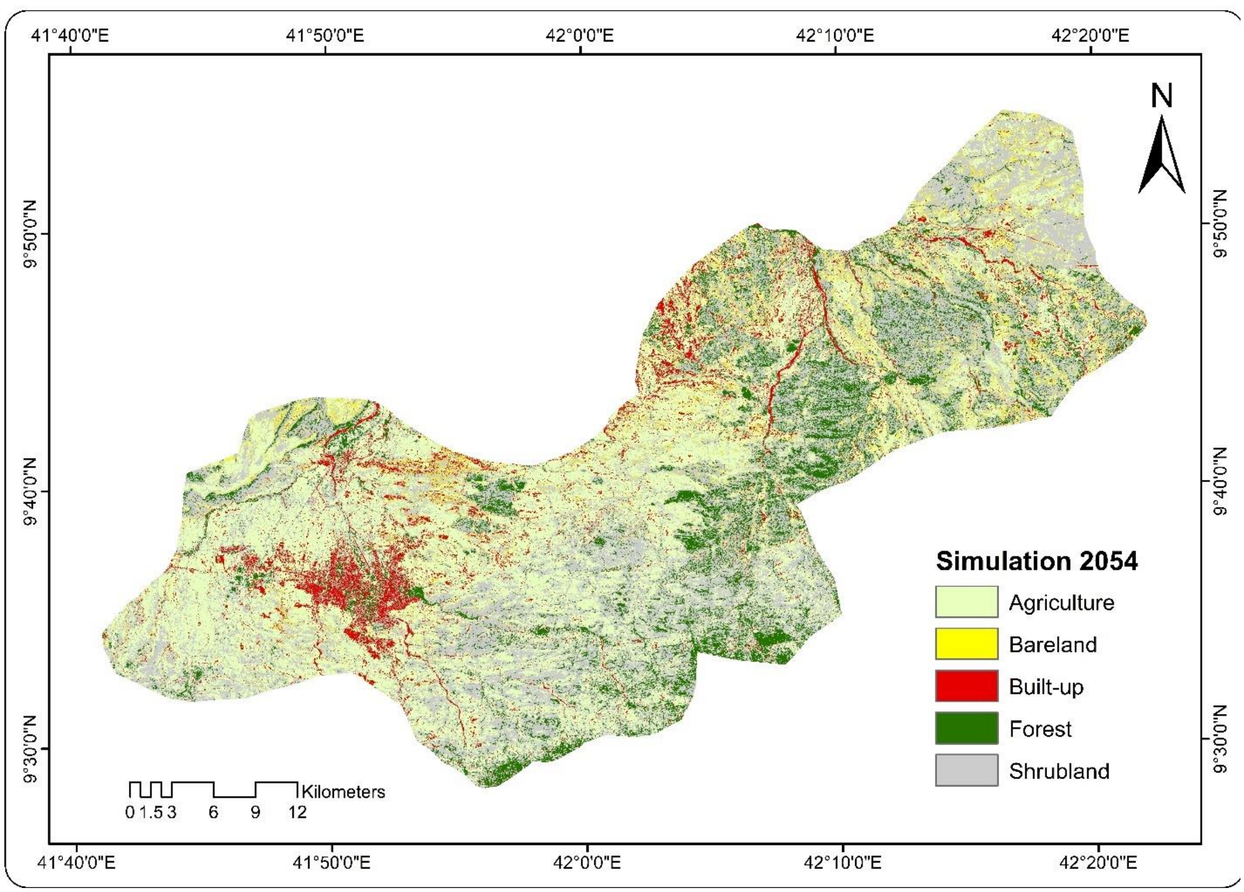


Figure 4-16: Simulation 2054

Table 4-10: LULC simulation result for the coming 2054 in Dire Dewa City

	2024		2054	
Class	Area (ha)	%	Area (ha)	%
Built-up	3377.19	2.20	10563.97	6.88
Agriculture	23241.20	15.14	59792.24	38.94
Forest	9764.43	6.36	16514.62	10.76
Shrubland	116104.59	75.61	60022.90	39.09
Bareland	1060.14	0.69	6653.79	4.33
Total	153547.55	100.00	153547.52	100.00

4.7.Discussions

The current study demonstrates that between 1994 and 2024, Dire Dawa has undergone profound land use and land cover (LULC) transformation—most notably the expansion of built-up areas from 0.07% to 2.2% and the reduction of forest land from 32.73% to 6.36%. These changes have been driven by a combination of rapid urbanization, agricultural expansion, and environmental degradation. The CA-Markov simulation for 2054 further projects this trend, with built-up areas expected to nearly triple again, reaching 6.88% of the city's area. These dynamics align closely with urban growth patterns observed in other studies applying the CA-Markov model, although most past studies have focused primarily on general LULC transitions without explicitly identifying informal settlement processes.

For instance, Beyene and Minale (2023) applied the CA-Markov model in Gondar City, Northwest Ethiopia, and observed a similar pattern of increased built-up land and reduced forest and shrubland due to urban expansion. Their model successfully forecasted urban growth but did not delve into the morphology or structure of that growth—particularly the extent to which it was formal or informal. Similarly, Belay et al. (2024), in their study of the Gumara Watershed, Upper Blue Nile Basin, identified considerable agricultural land expansion and degradation of forest cover but framed these transitions largely in environmental terms. In contrast, the Dire Dawa study extends beyond LULC classification and employs spatial landscape metrics (e.g., edge density, fractal dimension index, and compactness) to provide a nuanced understanding of how unregulated, informal settlement patterns emerge within these broader trends.

Moreover, the findings from Dire Dawa reinforce those from Gidey et al. (2017), who applied CA-Markov to predict LULC changes in Raya, Northern Ethiopia, and found a substantial increase in agricultural and built-up land at the expense of natural vegetation. However, Gidey et al.'s study—like most others—did not distinguish whether the urban expansion was formal or informal. This is a notable limitation in the broader CA-Markov literature, especially when addressing the realities of rapidly urbanizing cities in the Global South, where informal settlements account for a significant share of urban growth (UN-Habitat, 2020).

In this respect, the current study bridges a critical gap by integrating spatial metrics with CA-Markov modeling to detect and explain the nature of informal settlement expansion. The significant increases in edge density and fractal dimension index (FDI) in Zones 1, 6, 7, and 8 from 1994 to 2024 reflect increasingly fragmented and irregular land use—features that are well-documented indicators of informal settlement growth (Kuffer et al., 2014; Taubenböck et al., 2012). These metrics help differentiate between formal planned development and irregular, self-organized expansion, thus offering a clearer picture of urban informality in emerging secondary cities.

In addition, the steady rise in the Euclidean Nearest Neighbor (ENN) distances across multiple zones suggests a dispersed pattern of settlement growth, especially in peri-urban areas, often driven by land availability and weak regulatory oversight. This finding aligns with global studies indicating that informal settlements frequently develop in peri-urban areas with inadequate infrastructure and ambiguous land tenure (Satterthwaite, 2014; Turok & McGranahan, 2013). Unlike studies such as Gebresellase et al. (2023), which examined LULC trends in the Upper Awash Basin and highlighted environmental changes due to policy and climate interactions, the current study emphasizes socio-spatial transformations shaped by population growth, informal land markets, and planning failures.

Furthermore, the CA-Markov simulation for 2054 in Dire Dawa reveals not only an increase in built-up and agricultural land but also a dramatic decrease in shrubland—indicative of ecological stress and unsustainable land conversion. While this mirrors the findings of Belay et al. (2024) and Beyene and Minale (2023), who also noted vegetation loss due to anthropogenic pressures, this study uniquely highlights the spatial morphology of the expanding urban footprint. The use of compactness indices, for example, effectively distinguishes compact formal areas from sprawling, irregular informal settlements, offering insights critical for urban policy and land management.

Taken together, the Dire Dawa study contributes to a growing recognition that traditional CA-Markov applications—while powerful in forecasting land cover changes—must be complemented with spatial metrics to reveal the true complexity of urban growth in the Global South. The study illustrates how morphological indicators such as LPI and FDI can expose the underlying processes of informalization, helping to bridge the divide between land cover modeling and urban planning research.

The findings of this study also resonate strongly with the objectives outlined in key international frameworks such as the United Nations Sustainable Development Goals (SDGs) and the New Urban Agenda (NUA). Specifically, SDG 11 "Make cities and human settlements inclusive, safe, resilient, and sustainable" emphasizes the importance of managing urban expansion, reducing the growth of informal settlements, and promoting sustainable land use planning. The observed unregulated urban sprawl and the increasing prevalence of informal settlements in Dire Dawa pose a direct challenge to achieving targets such as 11.1, which aims for access to adequate, safe, and affordable housing, and 11.3, which promotes participatory and sustainable urbanization. Moreover, the study's use of spatial metrics and CA-Markov modeling provides a practical tool aligned with the New Urban Agenda's call for data-driven urban governance, allowing city authorities to monitor land transformations, identify informal growth hotspots, and implement targeted interventions. By integrating spatial forecasting with morphological analysis, this research contributes to the development of early-warning systems and urban monitoring frameworks advocated by global development agendas, thus supporting more equitable and forward-looking urban policy decisions.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATIONS

5.1.Conclusion

Over the past 30 years, the land use and land cover (LULC) in Dire Dawa City has undergone notable transformations driven by both natural and human factors. The area has experienced a significant reduction in forest and bare land, largely due to deforestation, agricultural expansion, and settlement growth. Agricultural land expanded during earlier periods but later declined as urbanization intensified and more land was allocated for settlements and infrastructure. Built-up areas have notably increased, reflecting rapid urban growth and the spread of informal settlements. The landscape metrics analyzed Edge Density (ED), Largest Patch Index (LPI), Fractal Dimension Index (FDI), and Euclidean Nearest Neighbor (ENN) collectively illustrate the spatial dynamics and morphological evolution of informal settlements from 1994 to 2024 across the eight urban zones. The steady rise in edge density across all zones, particularly in Zones 1, 6, 7, and 8, signals a significant increase in landscape fragmentation, commonly associated with the emergence of informal settlements characterized by irregular growth and unregulated development. Concurrently, the Largest Patch Index reveals the formation and consolidation of dominant built-up clusters in Zones 1 and 8, suggesting a transformation from scattered informal structures to more cohesive urban forms, often resulting from prolonged unplanned densification. The Fractal Dimension Index further supports this interpretation, showing rising spatial complexity especially in Zones 8, 7, and 1, indicative of the disordered and non-linear spatial patterns typically observed in self-organized informal neighborhoods. The CA-Markov model simulations reveal dynamic and significant shifts in land use and land cover in Dire Dawa between 1994 and the projected year 2054. The period from 1994 to 2024 shows extensive conversion to shrubland and a substantial decline in forest cover, reflecting trends of land degradation, urban encroachment, and agricultural pressure.

5.2.Recommendations

Based on the observed and projected land use and land cover changes in Dire Dawa City from 1994 to 2054, the following recommendations are proposed; -

- Given the increasing edge density and fractal complexity in Zones 1, 6, 7, and 8, regulatory measures and spatial planning are essential to manage unplanned urban growth and reduce landscape fragmentation.
- The marked increase in built-up areas and the consolidation of large settlement patches call for strict zoning enforcement and integrated planning to guide urban expansion sustainably.
- The sharp decline in forest and the spread of shrubland suggest ongoing vegetation degradation; reforestation and vegetation restoration programs should target areas with high transition to shrubland and bare land.
- Future research should integrate socio-economic and demographic data with spatial metrics to better understand the drivers of informal settlement growth and improve the predictive accuracy of CA-Markov models in urban contexts.

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